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Essays on Economic Integration

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Abstract

Essays on Economic Integration

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This dissertation consists of two chapters that account for the effects of economic integration between countries. Chapter I analyzed the causality between trade intensity and business cycle synchronization, and Chapter II captured the dynamic interdependence of stock returns.

Chapter I empirically researched whether the trade intensity, which was measured by value-added, could significantly explain the output comovement. Three types of trade intensities were constructed by using domestic value-added, total domestic value-added, and net returned domestic value-added, respectively. Using these, this dissertation conducted the empirical analyses based on Ordinary and Two Stage Least Squares for 43 countries from all over the world between 2000 and 2014. The main findings are summarized as follows. First, none of the trade intensities significantly explained the business cycle synchronization. Second, two intra-industry trades, which were constructed by the domestic value-added and total domestic value-added, significantly accounted for the output comovement. Third, the net returned domestic value-added was not important from the empirical point of view. In conclusion, the significant value-added trade channel on business cycle synchronization was not the trade intensity, but the intra-industry trade.

Chapter II measured whether the degree of interdependence of stock returns between China and Latin America has been changed over time. Based on the Dynamic Conditional Correlation Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) model, this dissertation documented dynamic changes of interdependence between 2003 and 2018. It then identified the relative importance of Chinese stock market on Latin America by comparing it to the interdependences between the United States and Latin America. The main results are as follows. First, the influence of Chinese stock on the Latin American stock market was not large although the economic relation between both regions has been strongly intensified over time. Second, Chile and Peru were more sensitive to the fluctuation of the Chinese stock return. Third, the stock returns of Latin America were heavily interconnected to the United States depite the enhanced economic relation between China and Latin America.

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Keywords: Economic Integration, Value-added, Trade Intensity, Business Cycle Synchronization, Stock Returns, DCC-MGARCH, China, Latin America
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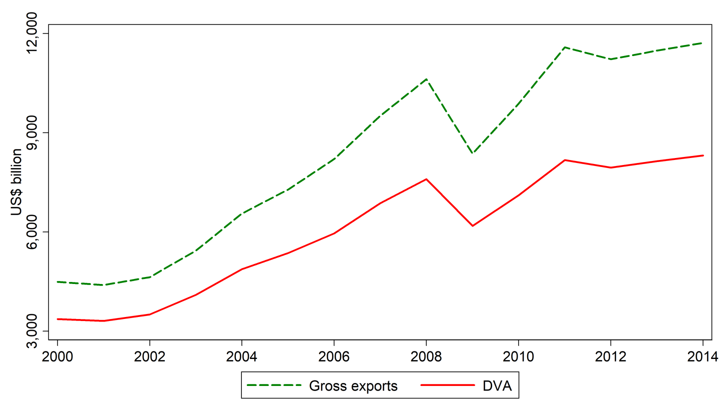
1 Reassessing the Causality between Value-added Trade Intensity and Business Cycle Synchronization

1.1 Introduction

Gross exports no longer capture its domestic value-added (DVA). By the enhanced international specialization of production networks, the gross exports tend to substantially overestimate its DVA.[1] As shown in Figure 1, the difference between gross exports and DVA increased 3.03 times from $1,123 billion in 2000 to $3,403 billion in 2014.



Source: Author's construction.
Note: The graphs are constructed by the World Input-Output Tables (WIOT) database released in 2016 that covers 28 European Union (EU) countries and 15 other major countries in the world, and classifies the 56 sectors according to the International Standard Industrial Classification (ISIC) Revision 4. The two lines are the sum of all 903 country-pairs.

Figure 1: Difference between Gross exports and DVA

Hence, it should be reassessed to find the causality between trade intensity and business cycle synchronization (BCS), which originated from Frankel and Rose (1998). For the first time, Johnson (2014) documented the relative importance between intermediate inputs and DVA on BCS.[2] By using a dynamic

[1] Johnson (2014) emphasized that using exports data recorded on a gross basis, not DVA, makes the economy look too open.

[2] Before Johnson (2014), several papers researched the effect of intermediate goods. Among others, see Burstein et al. (2008); Di Giovanni and Levchenko (2010); and Ng (2010).

multi-sector international real business cycle model, it concluded that the influential variable on the BCS was the intermediate inputs, not the DVA. On the contrary, Duval et al. (2016) theoretically introduced that the DVA was highly linked to BCS and empirically proved a positive effect of DVA trade intensity. However, Jeon (2018) found that the effect of DVA trade intensity varied depending on regions, because it was positive in European countries while unclear in East Asian countries. Rather, the intra-industry trade measured by DVA was positively significant for both regions. Though, according to Jiang et al. (2019), the DVA trade intensity had a positive effect on BCS for East Asia, and the effect of intra-industry trade was not robust depending on control variables.[3] That is, no consensus has yet been reached on the effect of DVA trade intensity as shown in Table 1.

Table 1: Summary of Empirical Literatures on DVA

PAPER	TYPE	N. OF COUNTRIES	PERIOD	T	IT	PROBLEM
Duval et al. (2016)	OLS and 2SLS	63	1995-2013	(+)	(?)	ME
Jeon (2018)	OLS	36	1995-2011	(?)	(+)	AB and OB
Jiang et al. (2019)	OLS	12	1995-2011	(+)	(?)	AB and SB

Source: Author's construction.
Note: N. is number, T is DVA trade intensity, and IT is DVA intra-industry trade. OLS and 2SLS denote Ordinary Least Squares and Two Stage Least Squares, respectively. (+) and (?) indicate a significantly positive and insignificant effect on BCS, respectively. ME is measurement error, AB is attenuation bias, OB is omitted variable bias, and SB is sample selection bias.

The inconsistent findings are mainly due to the following problems. First, an obvious measurement error (ME) was contained in the DVA of Johnson (2014) and Duval et al. (2016). Johnson (2014) assumed that the DVA was the function of only productivity and factor inputs, and the DVA and intermediate inputs were perfectly distinguished. In other words, any decomposition methodology for DVA was not used, and the DVA from intermediate transactions was thor-

[3]Note that it constructed the intra-industry trade by gross exports, not DVA.

oughly ignored.[4] Duval et al. (2016) used the actual DVA for only five years (1995, 2000, 2005, 2008 and 2009) of the total sample period from 1995 to 2013, meaning that a considerable ME was inherent.[5] Second, a serious omitted variable bias (OB) existed in Jeon (2018) as some of key factors on BCS were not included.[6] Third, DVA estimates of Jeon (2018) and Jiang et al. (2019) were contaminated by an attenuation bias (AB), because an endogeneity problem was not rectified. While Jeon (2018) did not consider the endogeneity at all, Jiang et al. (2019) tried to reduce it by one-year lagged variables. Nevertheless, as proven in Duval et al. (2016), using the lagged ones is not a suitable solution for the problem.[7] Fourth, a sample selection bias (SB) arised in Jiang et al. (2019), because the sample countries were limited to only 12 East Asian countries. As demonstrated by Jeon (2018), the DVA estimates considerably vary depending on sample regions.

On the basis of these problems, the main contributions of this paper are as follows. First of all, it removed a ME in DVA by adopting the decomposition methodology developed by Wang et al. (2013) to extract the pure amount of DVA from its gross exports. In addition, it applied the WIOT database in which the most industrial sectors existed, as more accurate DVA is able to be obtained from more segmented sectors. Second, it eliminated an OB by including all key factors on BCS. Also, it captured different growth dynamics and levels between countries by controlling additional variables.[8] Third, it removed

[4] DVA occurs in intermediate trade among countries. See the terms, which are DVA_INT, DVA_INTrexI1, DVA_INTrexF and DVA_INTrexI2, in Table 10 in Appendix 1.6.2.

[5] Duval et al. (2016) emphasized on the robustness of constructed DVA. However, DVA are influenced by the sort of ISIC Revision and number of countries and industries. Refer to Figure 2 in Appendix 1.6.1 about the ME in Duval et al. (2016).

[6] Jiang et al. (2019) documented that trade channel, financial intensity and similarity in production structure were the key factors on BCS. In particular, a large number of previous literatures documented that omitting the financial intensity caused a substantial bias in DVA estimates. Among others, see Kalemli-Ozcan et al. (2013a); Kalemli-Ozcan et al. (2013b); and Cesa-Bianchi et al. (2019).

[7] According to Duval et al. (2016), all estimates of DVA trade intensity in 2SLS model increased compared to those in OLS model, even though one-year lagged variables were applied in both models.

[8] The additional variables are from Duval et al. (2016), which are absolute difference in log

an AB by introducing new instrumental variable (IV), which was trade costs between countries. Fourth, it substantially reduced a SB by including 43 sample countries from all over the world.[9]

The remainder of this paper is organized as follows. Section 1.2 introduces the previous literatures about the causality between gross exports or DVA trade intensity and BCS. Section 1.3 describes the decomposition methodology and construction of data. Section 1.4 documents empirical results and interpretations. Section 1.5 draws implication.

1.2 Literature Review

Conducting a research on the causality between trade intensity and BCS has attracted a great attention since the seminal work by Frankel and Rose (1998), because it *ex post* justified the creation of an optimum currency area suggested by Mundell (1961). Through Ordinary Least Squares (OLS) and IV models for 21 industrial countries between 1959 and 1993, it found that the output comovement was positively affected by the bilateral trade intensity. Since then, numerous researches have been conducted to reassess the causal relationship, because the effect of trade intensity was theoretically ambiguous.[10]

Most of literatures have studied how gross exports trade intensity affected BCS, and most of them evaluated that the causality was robustly positive.[11]

PPP GDP per capita, product of log GDP, and product of log population.

[9]No more countries were included because the maximum number of countries offered by the WIOT database were 43.

[10]De Grauwe (2018) documented the two opposite stances which were the European comission view and Krugman view. On the one hand, the former perspective derived from Kenen (1969) and Emerson et al. (1992) asserted that an enhanced trade intensity led to more synchronized output comovement and to less frequent asymmetric shocks between countries where the proportion of intra-industry trade was large. On the other hand, the latter point of view supported by Eichengreen (1992) and Krugman (1993) reported that a strengthened trade intensity implied a higher inter-industry trade and led to the decline in the BCS between countries, in particular, when an idiosyncratic shock occured.

[11]Contrary literatures are as follows. Crosby (2003) examined the causal relationship for 13 countries in Asia-Pacific region for the period 1980-1999. The estimate of trade intensity did not account for synchronization phenomenon. Kumakura et al. (2005) documented that trade intensity did not lead to BCS while volume of trade was relevant to its own national

Otto et al. (2001) estimated the impact of trade in goods and services from 1960 to 2000 for 17 Organization for Economic Cooperation and Development (OECD) countries by OLS and IV models. It documented that an enhanced bilateral trade intensity made their business cycle more synchronized.[12] Clark and Van Wincoop (2001) analyzed the causality for 9 United States Census (USC) regions and 14 EU countries between 1963 and 1997 through OLS and IV models, and proved its positive sign on output correlation. Choe (2001) conducted the research on 10 East Asian countries for the two different sample periods, which were 1981-1990 and 1986-1995. It found that the greater bilateral trade relation, the stronger their BCS. Gruben et al. (2002) also supported a positive causal relationship between trade intensity and similarity in economic fluctuation. De Haan et al. (2002) addressed a positive effect of bilateral trade integration on BCS for 18 OECD countries over the year 1961-1997. Kose et al. (2003) examined an impact of trade intensity focusing on 21 developed and 55 developing countries from 1960 to 1999. Even though its degree was greater for the developed countries, the estimate for the developing countries was also positively relevant to similarity in output fluctuation. Shin and Sohn (2006) clustered 30 country-pairs for East Asian countries to figure out an effect of trade intensity on output, consumption and price correlation over the two sample periods, which were 1971-1996 and 1971-2003. While the consumption comovement was not connected to the trade intensity, both output and price comovements were positively affected. Unlike the above empirical studies, Kose and Yi (2006) tried to verify whether a standard international business cycle model was able to capture the causality or not. Even though its estimate was

economic fluctuation. In addition, how much electronic markets were exposed to the world was more important to BCS. Kalemli-Ozcan et al. (2013b) and Pescatori (2013) discovered that trade intensity was not able to explain output correlation when controlling country-pair factors in empirical models.

[12] However, in case of Australia and the United States, the significant variables were similarity of economic characteristics and institutions, not the degree of trade intensity.

smaller compared to the previous empirical findings, the effect of trade intensity obviously existed. Calderon et al. (2007) implemented a large scale of research for 147 countries from 1960 to 1999. It documented that a higher trading relation led to more synchronization phenomenon, and its estimate was higher for industrial countries than the other country-pairs, simliar to Kose et al. (2003). Inklaar et al. (2008) analyzed the causal relationship for 21 OECD countries between 1970 and 2003 by OLS and Three Stage Least Squares (3SLS) models. It was confirmed that the causality was positive and the estimate was not affected by outliers, even though its size was relatively smaller than the previous literatures, and it was not robust when considering quartiles in the model. Gianelle et al. (2017) addressed how trade volume and specialization affected to output comovement for the Economic and Monetary Union through OLS, 3SLS and seemingly unrelated regression models. The country-pairs, which had an enhanced trade relationship and similar economic structure, showed more synchronized output correlation. Paying attention to regional and global integration level, Gong and Kim (2018) conducted the reasearch for East Asia, Latin America, and Central and Eastern Europe. The regional trade integration was positively linked to BCS, and the effect was larger for the Central and Eastern Europe than the others.

On the other hand, several literatures have focused on trade structures between countries, specifically, on intra-industry trade. In general, the intra-industry trade reinforced BCS as indicated by De Grauwe (2018).[13] Kalemli-Ozcan et al. (2001) addressed an effect of industrial specialization on BCS for 11 OECD countries and 53 USC regions by OLS and IV models. It proved

[13]Contrary literatures are as follows. Gruben et al. (2002) denied a negative effect of industrial specialization on output comovement for 21 countries between 1965 and 1998. Burstein et al. (2008) documented that a trade structure in vertically integrated goods induced more synchronized output correlation. Di Giovanni and Levchenko (2010) reported an importance of vertical linkages among industrial sectors to account for BCS. The intra-industry trade was only able to explain 18% on BCS while the inter-industry trade accounted for 32%.

that a higher specialization was negatively connected to BCS for both regions. Shin and Wang (2003) conducted the research for 12 East Asian countries and found that the main channel on output correlation was a degree of intra-industry trade between countries. A trade intensity itself did not significantly affect to BCS.[14] Imbs (2004) discovered that an overall effect of bilateral trade was positive on output comovement, and the intra-industry trade accounted for most of the effect. Cortinhas (2007) researched an effect of intra-industry trade for 5 members of the Association of Southeast Asian Nations countries from 1962 to 1996 by two different models. The effect was not robust as a positive sign of intra-industry trade on BCS was confirmed in only one model. However, the result became highly significant and robust if excluding Indonesia from the sample countries and applying a panel data model. Rana (2008) extended the research of Shin and Wang (2004) by redefining a business cycle correlation model and adding more years to capture the effect of the Asian financial crisis. Despite these changes, a positive impact of intra-industry trade in East Asia was robustly valid. Rana et al. (2012) reported how bilateral trade structure affected to BCS for East Asian countries and European countries, respectively. For both regions, the key factor was the intra-industry trade, even though its size was larger in the East Asian countries. Saiki (2018) assessed an effect of trade intensity and intra-industry trade for East Asian and Eurozone. While the trade integration was ambiguously linked to BCS, the intra-industry trade rose the output comovement in both regions.

Lastly, a few literatures have recently started to focus on DVA trade intensity and DVA intra-industry trade. Johnson (2014) theoretically approached the relative role and importance of intermediate inputs and DVA on BCS. It found that the intermediate inputs were more important to explain the BCS,

[14] Through further researches, it was confirmed that the intra-industry trade was the key factor on BCS regardless of regions and periods. Refer to Shin and Wang (2004) and Shin and Wang (2005).

rather than the DVA. Duval et al. (2016) documented that DVA trade intensity highly led to output comovement for 63 Trade in Value Added (TiVA) countries between 1995 and 2013 by OLS and two types of IV models. In all models, the estimates of DVA trade intensity were robustly positive. Jeon (2018) reported a different estimates of DVA trade intensity on BCS for two regions. While the causality was positive in European countries, it was unclear in East Asian countries. Instead, DVA intra-industry trade was significantly positive for both regions. Jiang et al. (2019) discovered that DVA trade intensity had a positive impact on output comovement in 12 East Asian countries. However, the intra-industry trade, which was measured by gross exports, had no robust effect on BCS depending on control variables.

1.3 Data and Construction

Table 2: Major Input-Output Tables

Database	Period	N. of countries	N. of industries	Classification	Source
WIOT	2000-2014	43	56	ISIC Rev.4	EC
ICIO (TiVA)	2005-2015	64	36	ISIC Rev.4	OECD-WTO
Eora MRIO	1990-2015	190	26	ISIC Rev.3	ARC

Source: Author's construction.
Note: N. is number, Rev. is Revision, ICIO is Inter-Country Input-Output, MRIO is Multi-Region Input-Output, EC is European Commission, and ARC is Australian Research Council.

Among the major input-output tables summarized in Table 2,[15] this paper selected the WIOT database that provided the information about national accounts of countries and their cross-border transactions in 56 industrial sectors classified by the ISIC Revision 4.[16] Compared to the other databases, The advantages of WIOT are as follows. First of all, it provides the most segmented

[15]In addition to the databases introduced in Table 2, there are many databases such as Global Trade Analysis Project, Asian International Input-Output Tables, or Asian Development Bank, multi-regional input-output tables. However, these databases were excluded because they did not provide consecutive yearly time series data.
[16]For the explanation of 56 industrial sectors, refer to Table 11 in Appendix 1.6.3.

industrial sectors, which means that the most accurate DVA can be measured. Second, a large number of observations can be obtained because it has relatively long time series data. Consequently, this paper covered the 43 countries from all over the world between 2000 and 2014 in the WIOT database to address the effect of DVA trade intensity on BCS.[17]

1.3.1 Business Cycle Synchronization

In order to capture the degree of BCS between country i and j at time t, the instantaneous quasi-correlation coefficient of real GDP growth rate (BCS_{ijt}) was calculated as

$$BCS_{ijt} = \frac{(g_{it} - \bar{g}_i)(g_{jt} - \bar{g}_j)}{\sigma_i \sigma_j},$$

where g_{it} was the difference in logarithm of country i's real GDP at time t, and $\bar{g}_i$ and σ_i denoted the sample period mean and standard deviation of real GDP growth rate of country i. The data was obtained from the World Economic Outlook (WEO). As Duval et al. (2016) documented, using the quasi-correlation coefficient has the following advantages. First, it is able to lower the artificial autocorrelation problem compared to other indicators such as a rolling Pearson correlation coefficient. Second, since there is no constraint that the coefficient should be bounded between -1 and 1, the error terms are relatively normal in empirical models than the Person correlation coefficient.

1.3.2 Trade Channel

The trade channel was composed of two variables that were trade intensity and intra-industry trade. Since they were measured by DVA, not gross exports, this

[17] The countries consist of 28 European countries (Austria, Belgium, Bulgaria, Cyprus, Czech, Denmark, Estonia, Finland, France, Germany, Greece, Croatia, Hungary, Ireland, Italia, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and United Kingdom) and 15 other countries from all over the world (Australia, Brazil, Canada, China, India, Indonesia, Japan, Korea, Mexico, Norway, Russia, Switzerland, Taiwan, Turkey and the United States).

paper introduces how to extract the pure amount of DVA from its gross exports before describing how to construct the variables.

First of all, the decomposition methodology developed by Wang et al. (2013) was applied in order to find the amount of DVA. Unlike the other methodologies such as Johnson and Noguera (2012) or Koopman et al. (2014), Wang et al. (2013) guarantees the aggregate consistency of DVA at bilateral level.[18] For a general description of the decomposition procedure, this paper assumed that transactions in the world consisted of N countries and K industries. The decomposition matrix was defined as

$$\begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^N \end{bmatrix} = \begin{bmatrix} Z^{11} & Z^{12} & \cdots & Z^{1N} \\ Z^{21} & Z^{22} & \cdots & Z^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ Z^{N1} & Z^{N2} & \cdots & Z^{NN} \end{bmatrix} + \begin{bmatrix} \sum_{r=1}^{N} Y^{1r} \\ \sum_{r=1}^{N} Y^{2r} \\ \vdots \\ \sum_{r=1}^{N} Y^{Nr} \end{bmatrix}, \tag{1}$$

where X^s was the $K \times 1$ industrial output vector of country $s \in N$, Z^{sr} was the $K \times K$ industrial intermediate transaction matrix of country s to $r \in N$, and Y^{sr} was the $K \times 1$ industrial final demand vector of country s to r. Equation (1) was rewritten as

$$\begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^N \end{bmatrix} = \begin{bmatrix} A^{11} & A^{12} & \cdots & A^{1N} \\ A^{21} & A^{22} & \cdots & A^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ A^{N1} & A^{N2} & \cdots & A^{NN} \end{bmatrix} \begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^N \end{bmatrix} + \begin{bmatrix} Y^1 \\ Y^2 \\ \vdots \\ Y^N \end{bmatrix}, \tag{2}$$

where A^{sr} was the $K \times K$ input coefficient matrix of country s to r, and Y^s was the $K \times 1$ global final demand vector of country s. By using the Leontief

[18] The bilateral sum of DVA, which is derived by the other methodologies, is able to exceed the bilateral gross exports.

inverse matrix to Equation (2), it was organized as

$$\begin{bmatrix} X^1 \\ X^2 \\ \vdots \\ X^N \end{bmatrix} = \begin{bmatrix} I - A^{11} & -A^{12} & \cdots & -A^{1N} \\ -A^{21} & I - A^{22} & \cdots & -A^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ -A^{N1} & -A^{N2} & \cdots & I - A^{NN} \end{bmatrix}^{-1} \begin{bmatrix} Y^1 \\ Y^2 \\ \vdots \\ Y^N \end{bmatrix}, \tag{3}$$

where I was the $K \times K$ identity matrix. From Equation (3), the $K \times K$ output multiplier matrix of country s to r (B^{sr}) was obtained as

$$\begin{bmatrix} B^{11} & B^{12} & \cdots & B^{1N} \\ B^{21} & B^{22} & \cdots & B^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ B^{N1} & B^{N2} & \cdots & B^{NN} \end{bmatrix} = \begin{bmatrix} I - A^{11} & -A^{12} & \cdots & -A^{1N} \\ -A^{21} & I - A^{22} & \cdots & -A^{2N} \\ \vdots & \vdots & \ddots & \vdots \\ -A^{N1} & -A^{N2} & \cdots & I - A^{NN} \end{bmatrix}^{-1},$$

and the $K \times K$ domestic Leontief inverse matrix of country r (L^{rr}) and the $1 \times K$ DVA coefficient vector of country s (V^s) were respectively calculated as $L^{rr} = (I - A^{rr})^{-1}$ and $V^s = [1\ 1\ \cdots\ 1] - \sum_{n=1}^{N} \sum_{j,k=1}^{K} B_{jk}^{ns}$.[19] In conclusion,

[19] For the detailed decomposition procedure, refer to Wang et al. (2013).

the 16 terms were derived as

$$
\begin{aligned}
\text{DVA\_FIN} &= (V^s B^{ss})^T \cdot Y^{sr}, \\
\text{DVA\_INT} &= (V^s L^{ss})^T \cdot (A^{sr} B^{rr} Y^{rr}), \\
\text{DVA\_INTrexI1} &= (V^s L^{ss})^T \cdot (A^{sr} \textstyle\sum_{t \neq s,r}^{N} B^{rt} Y^{tt}), \\
\text{DVA\_INTrexF} &= (V^s L^{ss})^T \cdot (A^{sr} B^{rr} \textstyle\sum_{t \neq s,r}^{N} Y^{rt}), \\
\text{DVA\_INTrexI2} &= (V^s L^{ss})^T \cdot (A^{sr} \textstyle\sum_{t \neq s,r}^{N} B^{rt} \textstyle\sum_{u \neq s,t}^{N} Y^{tu}), \\
\text{RDV\_FIN} &= (V^s L^{ss})^T \cdot (A^{sr} B^{rr} Y^{rs}), \\
\text{RDV\_FIN2} &= (V^s L^{ss})^T \cdot (A^{sr} \textstyle\sum_{t \neq s,r}^{N} B^{rt} Y^{ts}), \\
\text{RDV\_INT} &= (V^s L^{ss})^T \cdot (A^{sr} B^{rs} Y^{ss}), \\
\text{DDC\_FIN} &= (V^s L^{ss})^T \cdot (A^{sr} B^{rs} \textstyle\sum_{t \neq s}^{N} Y^{st}), \\
\text{DDC\_INT} &= (V^s L^{ss} \textstyle\sum_{t \neq s}^{N} A^{st} B^{ts})^T \cdot (A^{sr} X^{r}), \\
\text{MVA\_FIN} &= (V^r B^{rs})^T \cdot Y^{sr}, \\
\text{OVA\_FIN} &= (\textstyle\sum_{t \neq s,r}^{N} V^t B^{ts})^T \cdot Y^{sr}, \\
\text{MVA\_INT} &= (V^r B^{rs})^T \cdot (A^{sr} L^{rr} Y^{rr}), \\
\text{OVA\_INT} &= (\textstyle\sum_{t \neq s,r}^{N} V^t B^{ts})^T \cdot (A^{sr} L^{rr} Y^{rr}), \\
\text{MDC} &= (V^r B^{rs})^T \cdot (A^{sr} L^{rr} E^{r*}), \\
\text{ODC} &= (\textstyle\sum_{t \neq s,r}^{N} V^t B^{ts})^T \cdot (A^{sr} L^{rr} E^{r*}),
\end{aligned}
\tag{4}
$$

where E^{r*} was the gross exports of country r, and $\cdot$ denoted the element-wise multiplication operator.[20]

Second, the trade intensity and intra-industry trade measured by DVA were constructed in three ways depending on the combination of derived terms in Equation (4). Firstly, the DVA trade intensity (T_{ijt}) and DVA intra-industry

[20] This paper decomposed gross exports into the 16 terms in Equation (4) using the R-package by Quast and Kummritz (2015).

trade (IT_{ijt}) between country i and j at time t were constructed as

$$T_{ijt} = \ln\left(\frac{V_{ijt} + V_{jit}}{Y_{it} + Y_{jt}}\right) \quad \text{and} \quad IT_{ijt} = 1 - \frac{\sum_{k=1}^{K} |V_{ijt}^k - V_{jit}^k|}{\sum_{k=1}^{K} (V_{ijt}^k + V_{jit}^k)},$$

where V_{ijt} was the DVA, which was the aggregate of DVA_FIN, DVA_INT, DVA_INTrexI1, DVA_INTrexF and DVA_INTrexI2, from country i to j at time t, Y_{it} was the nominal GDP of country i at time t, and V_{ijt}^k was the DVA of country i to j in industrial sector k at time t. By the definition, the DVA trade intensity takes a negative form. The closer the variable is to 0, the higher the DVA trade intensity is. The DVA intra-industry trade is set at values between 0 and 1.[21] The closer the variable is to 1, the stronger the DVA intra-industry trade is. Secondly, the total DVA trade intensity (T_{ijt}^t) and total DVA intra-industry trade (IT_{ijt}^t) between country i and j at time t were defined as

$$T_{ijt}^t = \ln\left(\frac{O_{ijt} + O_{jit}}{Y_{it} + Y_{jt}}\right) \quad \text{and} \quad IT_{ijt}^t = 1 - \frac{\sum_{k=1}^{K} |O_{ijt}^k - O_{jit}^k|}{\sum_{k=1}^{K} (O_{ijt}^k + O_{jit}^k)},$$

where O_{ijt} was the total DVA, which consisted of DVA, RDV_FIN, RDV_FIN2 and RDV_INT, from country i to j at time t, and O_{ijt}^k was the total DVA of country i to j in industrial sector k at time t. The reason why this paper constructed the trade channel by DVA and total DVA, respectively, is because a theoretical effect on the three terms, which are RDV_FIN, RDV_FIN2 and RDV_INT, is not clearly established. For example, Duval et al. (2016) documented that the above three terms should be included in DVA, while Jeon (2018) insisted that they should be eliminated as they generated wrong information about where DVA in exports was finally consumed. Thus, this paper considered the two types of trade channel to confirm whether the distinction between DVA and total DVA was important from an empirical point of view.

[21] In few cases, the DVA intra-industry trade had a negative value because DVA could be less than zero.

Thirdly, the net returned DVA (RDV) trade intensity (T^r_{ijt}) and net RDV intra-industry trade (IT^r_{ijt}) between country i and j at time t were described as

$$T^r_{ijt} = \ln\left(\frac{R_{ijt} + R_{jit}}{Y_{it} + Y_{jt}}\right) \quad \text{and} \quad IT^r_{ijt} = 1 - \frac{\sum_{k=1}^{K} |R^k_{ijt} - R^k_{jit}|}{\sum_{k=1}^{K}(R^k_{ijt} + R^k_{jit})},$$

where R_{ijt} was the net RDV, which was the aggregate of RDV_FIN, RDV_FIN2 and RDV_INT, from country i to j at time t, and R^k_{ijt} was the net RDV of country i to j in industrial sector k at time t. This paper removed the DDC_FIN and DDC_INT, which were the other terms in RDV, because they were the double counting terms. The trade channel measured by the net RDV was to empirically verify whether the three terms, which were theoretically unclear, was significant.

Table 3: Descriptive Statistics

	Obs.	**Mean**	**Std.**	**Min.**	**P25**	**P50**	**P75**	**Max.**	**Skew.**	**Kurt.**
BCS	13,545	0.52	1.48	-7.68	-0.04	0.14	0.57	10.22	3.34	16.66
T	13,545	-7.17	1.69	-13.95	-8.19	-6.98	-6.00	-3.26	-0.46	2.99
T^t	13,545	-7.17	1.70	-13.95	-8.12	-6.98	-5.99	-3.23	-0.45	2.98
T^r	13,545	-13.19	2.75	-22.70	-15.08	-13.16	-11.29	-5.66	-0.14	2.74
IT	13,545	0.33	0.18	-0.55	0.19	0.31	0.46	0.90	0.23	2.36
IT^t	13,545	0.33	0.18	-0.54	0.19	0.31	0.46	0.86	0.23	2.35
IT^r	13,545	0.22	0.18	-0.00	0.05	0.18	0.35	0.84	0.67	2.47
F	7,642	-6.38	2.49	-16.27	-7.95	-6.30	-4.47	-0.35	-0.45	3.17
SI	13,545	-0.61	0.18	-1.32	-0.71	-0.59	-0.48	-0.19	-0.62	3.41
ABS^*	13,545	0.66	0.56	0.00	0.23	0.52	0.92	3.45	1.37	4.96
GDP^*	13,545	701.13	66.16	498.26	653.98	702.28	747.75	914.12	-0.04	2.69
POP^*	13,545	278.56	43.54	166.78	247.35	275.94	305.25	441.07	0.36	3.00

Note: Obs. is observation, Std. is standard error, P is percentile, Min. is minimum, Max. is maximum, Skew. is skewness, and Kurt. is kurtosis.

1.3.3 Control Variables

By the following two criteria, this paper included the additional control variables. First, as already mentioned, the financial intensity and similarity in production structure, which are the key factors on BCS, should not be excluded. The financial intensity (F_{ijt}) between country i and j at time t was defined as

$$F_{ijt} = \ln\left(\frac{P_{ijt} + P_{jit}}{Y_{it} + Y_{jt}}\right),$$

where P_{ijt} was the portfolio investment from country i to j at time t. The data was obtained from the Coordinated Portfolio Investment Survey (CPIS). By the definition, the financial intensity has a negative value. The closer the variable is to 0, the higher the financial intensity is. The similarity in production structure (SI_{ijt}) between country i and j at time t was described as

$$SI_{ijt} = -\sum_{k=1}^{K} |S_{it}^{k} - S_{jt}^{k}|,$$

where S_{it}^{k} was the share of industrial sector k in the real GDP of country i at time t. The closer the variable is to 0, the higher the similarity in production structure is. Second, the control variables used in Duval et al. (2016) were introduced.[22] The product of log real GDP (GDP_{ijt}^{*}) and the product of log population (POP_{ijt}^{*}) between country i and j at time t were repectively defined as

$$GDP_{ijt}^{*} = \ln Y_{it} \times \ln Y_{jt} \quad \text{and} \quad POP_{ijt}^{*} = \ln P_{it}^{*} \times \ln P_{jt}^{*},$$

where P_{it}^{*} was the population of country i at time t. The absolute difference in log PPP GDP per capita (ABS_{ijt}^{*}) between country i and j at time t was

[22] Since the main purpose of this paper is to reassess the causality between DVA trade intensity and BCS, there should not exist a big difference in the selection of variables. As Duval et al. (2016) was considered appropriate for comparison with the results from this paper, the variables used in Duval et al. (2016) were applied.

constructed as

$$ABS^{*}_{ijt} = |\ln y_{it} - \ln y_{jt}|,$$

where y_{it} was the PPP GDP per capita of country i at time t. The above additional variables were obtained from the WEO.

The descriptive statistics are summarized in Table 3, and two results are the most noticeable. Firstly, there was little difference between the descriptive statistics of DVA and total DVA trade intensity, and DVA and total DVA intra-industry trade. It means that the difference between DVA and total DVA may not empirically be important. Second, the number of samples for financial intensity was relatively low compared to the other variables, because the financial data for developing countries were not readily available.

1.4 Models and Results

To reassess the causality between the DVA trade intensity and BCS, this paper performed the two types of empirical analysis, which were the OLS and IV regressions.

1.4.1 OLS Estimates

This paper constructed the OLS regression models based on the following baseline formula.

$$BCS_{ijt} = \alpha_{ij} + \alpha_t + f(\mathbf{\Gamma}_{ijt}, \mathbf{\Delta}_{ijt}, \mathbf{\Omega}_{ijt}) + \epsilon_{ijt},$$

where α_{ij} was the country-pair fixed effect that captured unobservable time-invariant fixed factors of country-pair i and j, and α_t was the time effect that controlled time-varying common factors. $\mathbf{\Gamma}_{ijt}$ and $\mathbf{\Delta}_{ijt}$ standed for a vector of trade intensities and intra-industry trades between country i and j at time t, respectively. $\mathbf{\Omega}_{ijt}$ denoted a vector of control variables between country i and j at time t. Since the autocorrelation and arbitrary heteroskedasticity were strongly suspected due to the nature of country-pair and time series data, the error terms (ϵ_{ijt}) between country i and j at time t were clustered at country-pair level.

Table 4: OLS Estimates (DVA)

	OLS	OLS	OLS	OLS
Dependent variable: BCS_{ijt}	(1)	(2)	(3)	(4)
DVA trade intensity (T_{ijt})	-0.069**	-0.050	-0.035	-0.048
	(0.035)	(0.036)	(0.037)	(0.038)
DVA intra-industry trade (IT_{ijt})	0.815***	0.827***	0.861***	0.849***
	(0.179)	(0.178)	(0.180)	(0.180)
Financial intensity (F_{ijt})	-0.099***	-0.088***	-0.089***	-0.093***
	(0.015)	(0.015)	(0.015)	(0.016)
Similarity in production structure (SI_{ijt})	0.302	0.489	0.615*	0.668*
	(0.322)	(0.321)	(0.343)	(0.341)
Product of log GDP (GDP^{*}_{ijt})		-0.009***	-0.010***	-0.013***
		(0.002)	(0.002)	(0.002)
Product of log population (POP^{*}_{ijt})			0.033**	0.041***
			(0.014)	(0.014)
Absolute difference in log PPP GDP per capita (ABS^{*}_{ijt})				-0.295**
				(0.143)
Year-effects	Yes	Yes	Yes	Yes
Country-pair effects	Yes	Yes	Yes	Yes
Observations	7,642	7,642	7,642	7,642
Adjusted R^2	0.748	0.748	0.748	0.749

Note: ***, ** and * denote the 1%, 5% and 10% significance levels, respectively.

First of all, the OLS estimates of DVA trade intensity on BCS are presented in Table 4. Only except for the column (1), all estimates of DVA trade intensity were insignificant even at 10% level. On the other hand, the DVA intra-industry trade had a positive and robust impact on BCS at 1% significance level in all columns. As for the key factors, the estimates of financial intensity were robustly negative similar to most of previous literatures.[23] In case of the similarity in production structure, the estimates were only significant at 10% level in the columns (3) and (4).

[23]The higher the financial intensity is, the easier the capital movement is to a country with high return on capital. In addition, capital flows to relatively stable country are expected to occur when common shocks arise.

Table 5: OLS Estimates (Total DVA)

Dependent variable: BCS_{ijt}	OLS (1)	OLS (2)	OLS (3)	OLS (4)
Total DVA trade intensity (T^t_{ijt})	-0.069**	-0.050	-0.035	-0.048
	(0.035)	(0.036)	(0.037)	(0.038)
Total DVA intra-industry trade (IT^t_{ijt})	0.833***	0.844***	0.878***	0.867***
	(0.178)	(0.177)	(0.179)	(0.179)
Financial intensity (F_{ijt})	-0.099***	-0.088***	-0.089***	-0.093***
	(0.015)	(0.015)	(0.015)	(0.016)
Similarity in production structure (SI_{ijt})	0.300	0.487	0.613*	0.666*
	(0.322)	(0.321)	(0.343)	(0.341)
Product of log GDP (GDP^*_{ijt})		-0.009***	-0.010***	-0.013***
		(0.002)	(0.002)	(0.002)
Product of log population (POP^*_{ijt})			0.033**	0.041***
			(0.014)	(0.015)
Absolute difference in log PPP GDP per capita (ABS^*_{ijt})				-0.295**
				(0.143)
Year-effects	Yes	Yes	Yes	Yes
Country-pair effects	Yes	Yes	Yes	Yes
Observations	7,642	7,642	7,642	7,642
Adjusted R^2	0.748	0.748	0.748	0.749

Note: ***, ** and * denote the 1%, 5% and 10% significance levels, respectively.

Second, Table 5 reports the OLS estimates of total DVA trade intensity on BCS. The most noticeable finding was that there was no difference in the estimates and robust standard errors of trade intensities between Table 4 and 5. That is to say, whether using DVA or total DVA was not important from an empirical point of view. Though, the effects of overestimation were found in the other trade channel, which was intra-industry trade. Nevertheless, the magnitude of difference between DVA and total DVA intra-industry trade was so small enough to be ignored.

Third, the OLS estimates of net RDV trade intensity are shown in Table 6. Like the DVA and total DVA trade intensities, the estimates of net RDV trade intensity were also insignificant even at 10% level only except for the column (1). However, as opposed to the previous two results, the net RDV intra-industry trade had no significant effect on BCS in all columns.[24]

[24]Even though Duval et al. (2016) theoretically emphasized that RDV was an important factor on BCS, its effectiveness has not empirically been proven in this paper.

Table 6: OLS Estimates (Net RDV)

Dependent variable: BCS_{ijt}	OLS (1)	OLS (3)	OLS (5)	OLS (7)
Net RDV trade intensity (T^{r}_{ijt})	-0.040*	-0.021	-0.014	-0.019
	(0.021)	(0.022)	(0.023)	(0.023)
Net RDV intra-industry trade (IT^{r}_{ijt})	0.151	0.136	0.153	0.124
	(0.156)	(0.155)	(0.154)	(0.155)
Financial intensity (F_{ijt})	-0.098***	-0.087***	-0.087***	-0.092***
	(0.015)	(0.015)	(0.015)	(0.016)
Similarity in production structure (SI_{ijt})	0.459	0.646**	0.759**	0.813**
	(0.317)	(0.316)	(0.340)	(0.339)
Product of log GDP (GDP^{*}_{ijt})		-0.009***	-0.010***	-0.012***
		(0.002)	(0.002)	(0.002)
Product of log population (POP^{*}_{ijt})			0.029**	0.036***
			(0.014)	(0.014)
Absolute difference in log PPP GDP per capita (ABS^{*}_{ijt})				-0.273**
				(0.139)
Year-effects	Yes	Yes	Yes	Yes
Country-pair effects	Yes	Yes	Yes	Yes
Observations	7,642	7,642	7,642	7,642
Adjusted R^2	0.747	0.748	0.748	0.748

Note: ***, ** and * denote the 1%, 5% and 10% significance levels, respectively.

1.4.2 IV Estimates

So far, this paper analyzed the causality between trade intensity and BCS by using the OLS models that have been adopted in a majority of previous studies. However, the OLS models do not correct problems occurred by an endogeneity. The two representative examples are as follows. Firstly, BCS is able to affect trade intensity. For instance, rapid economic growth in both countries can promote more active trade transaction between them. Secondly, the relation between BCS and trade intensity can be simultaneously connected via its error terms. For these reasons, this paper additionally performed IV regressions to correct a possibility of attenuation bias. The baseline Two Stage Least Squares (2SLS) model was constructed as

$$\mathbf{\Gamma}_{ijt} = \beta_{ij} + \beta_t + f(Z_{ijt},\, \mathbf{\Delta}_{ijt},\, \mathbf{\Omega}_{ijt}) + u_{ijt}, \tag{5}$$

$$BCS_{ijt} = \alpha_{ij} + \alpha_t + f(\mathbf{\Gamma}_{ijt},\, \mathbf{\Delta}_{ijt},\, \mathbf{\Omega}_{ijt}) + \epsilon_{ijt}, \tag{6}$$

where Z_{ijt} was the trade costs between country i and j at time t, and u_{ijt} was the error terms between country i and j at time t. The IV, which was the trade costs, was obtained from the ESCAP-World Bank Trade Costs database, and consisted of three subcategories, which were transport costs, border related trade barriers and retail and wholesale distribution costs.[25] Since BCS has little effects on the components of trade costs compared to trade intensity, it is appropriate IV for the model. In addition, while the Pearson correlation coefficient between trade costs and error terms was only -0.08, that between trade costs and trade intensity was -0.81.

Table 7: IV Estimates (DVA)

	IV	IV	IV	IV
Dependent variable: BCS_{ijt}	(1)	(2)	(3)	(4)
DVA trade intensity (T_{ijt})	0.031	0.075	0.099	0.082
	(0.112)	(0.115)	(0.127)	(0.137)
DVA intra-industry trade (IT_{ijt})	0.987***	1.029***	1.054***	1.042***
	(0.217)	(0.217)	(0.222)	(0.224)
Financial intensity (F_{ijt})	-0.103***	-0.090***	-0.092***	-0.094***
	(0.020)	(0.020)	(0.020)	(0.020)
Similarity in production structure (SI_{ijt})	0.454	0.649**	0.729**	0.746**
	(0.326)	(0.330)	(0.347)	(0.346)
Product of log GDP (GDP^*_{ijt})		-0.010***	-0.011***	-0.012***
		(0.002)	(0.003)	(0.003)
Product of log population (POP^*_{ijt})			0.020	0.024
			(0.024)	(0.023)
Absolute difference in log PPP GDP per capita (ABS^*_{ijt})				-0.161
				(0.201)
Year-effects	Yes	Yes	Yes	Yes
Country-pair effects	Yes	Yes	Yes	Yes
Observations	6,906	6,906	6,906	6,906
Adjusted R^2	0.742	0.742	0.742	0.742

Note: ***, ** and * denote the 1%, 5% and 10% significance levels, respectively.

First of all, the IV estimates of DVA trade intensity on BCS are presented in Table 7. Since all estimates of DVA trade intensity increased compared to Table 4, it was concluded that the attenuation bias was correctly rectified. Nevertheless, the estimates were insignificant even at 10% level. Thus, it can

[25] Each subcategory has following components. Transport costs have freight costs and transit costs. Border related trade barriers consist of policy barriers (tariff and non-tariff barriers), language barrier, currency barrier, information costs barrier and security barrier.

be concluded that the trade intensity had no significant effect on BCS. On the other hand, the DVA intra-industry trade had still positive and significant effect even at 1% level. Compared to results of Table 4, the estimates slightly increased. As for the key factors, while the estimates of financial intensity showed substantially similar results to Table 4, the significance level of similarity in production structure increased from 10% to 5% except for the column (1).

Table 8: IV Estimates (Total DVA)

	IV	IV	IV	IV
Dependent variable: BCS_{ijt}	(1)	(2)	(3)	(4)
Total DVA trade intensity (T^t_{ijt})	0.031	0.074	0.099	0.081
	(0.112)	(0.115)	(0.127)	(0.137)
Total DVA intra-industry trade (IT^t_{ijt})	1.011***	1.053***	1.078***	1.066***
	(0.217)	(0.218)	(0.222)	(0.224)
Financial intensity (F_{ijt})	-0.103***	-0.090***	-0.092***	-0.094***
	(0.020)	(0.020)	(0.020)	(0.020)
Similarity in production structure (SI_{ijt})	0.450	0.646*	0.726**	0.743**
	(0.326)	(0.330)	(0.347)	(0.346)
Product of log GDP (GDP^*_{ijt})		-0.010***	-0.011***	-0.012***
		(0.002)	(0.003)	(0.003)
Product of log population (POP^*_{ijt})			0.021	0.024
			(0.024)	(0.023)
Absolute difference in log PPP GDP per capita (ABS^*_{ijt})				-0.161
				(0.201)
Year-effects	Yes	Yes	Yes	Yes
Country-pair effects	Yes	Yes	Yes	Yes
Observations	6,906	6,906	6,906	6,906
Adjusted R^2	0.742	0.742	0.742	0.742

Note: ***, ** and * denote the 1%, 5% and 10% significance levels, respectively.

Second, Table 8 reports the IV estimates of total DVA trade intensity on BCS. Like the results of Table 4 and 5, there was little difference in the estimates and robust standard errors between DVA and total DVA trade intensity even using the IV model. Thus, from an empirical point of view, the trade intensity constructed by total DVA was not able to overestimate the results from DVA trade intensity.

Third, the IV estimates of net RDV trade intensity were shown in Table 9. The IV model increased the estimates of net RDV trade intensity, but they were still insignificant even at 10% level. Also, the net RDV intra-industry trade

Table 9: IV Estimates (Net RDV)

Dependent variable: BCS_{ijt}	IV (1)	IV (2)	IV (3)	IV (4)
Net RDV trade intensity (T^r_{ijt})	0.025	0.053	0.065	0.053
	(0.070)	(0.074)	(0.081)	(0.137)
Net RDV intra-industry trade (IT^r_{ijt})	0.279	0.269	0.285	0.255
	(0.204)	(0.204)	(0.208)	(0.214)
Financial intensity (F_{ijt})	-0.102***	-0.088***	-0.089***	-0.091***
	(0.019)	(0.019)	(0.019)	(0.019)
Similarity in production structure (SI_{ijt})	0.630*	0.834**	0.894***	0.912***
	(0.324)	(0.330)	(0.347)	(0.346)
Product of log GDP (GDP^*_{ijt})		-0.011***	-0.011***	-0.012***
		(0.003)	(0.003)	(0.003)
Product of log population (POP^*_{ijt})			0.015	0.018
			(0.022)	(0.023)
Absolute difference in log PPP GDP per capita (ABS^*_{ijt})				-0.166
				(0.191)
Year-effects	Yes	Yes	Yes	Yes
Country-pair effects	Yes	Yes	Yes	Yes
Observations	6,906	6,906	6,906	6,906
Adjusted R^2	0.741	0.741	0.741	0.741

Note: ***, ** and * denote the 1%, 5% and 10% significance levels, respectively.

had no significant impact on BCS. Though, the effects of financial intensity were significant at 1% level, and the similarity in production structure was also significant in all columns.

1.5 Concluding Remarks

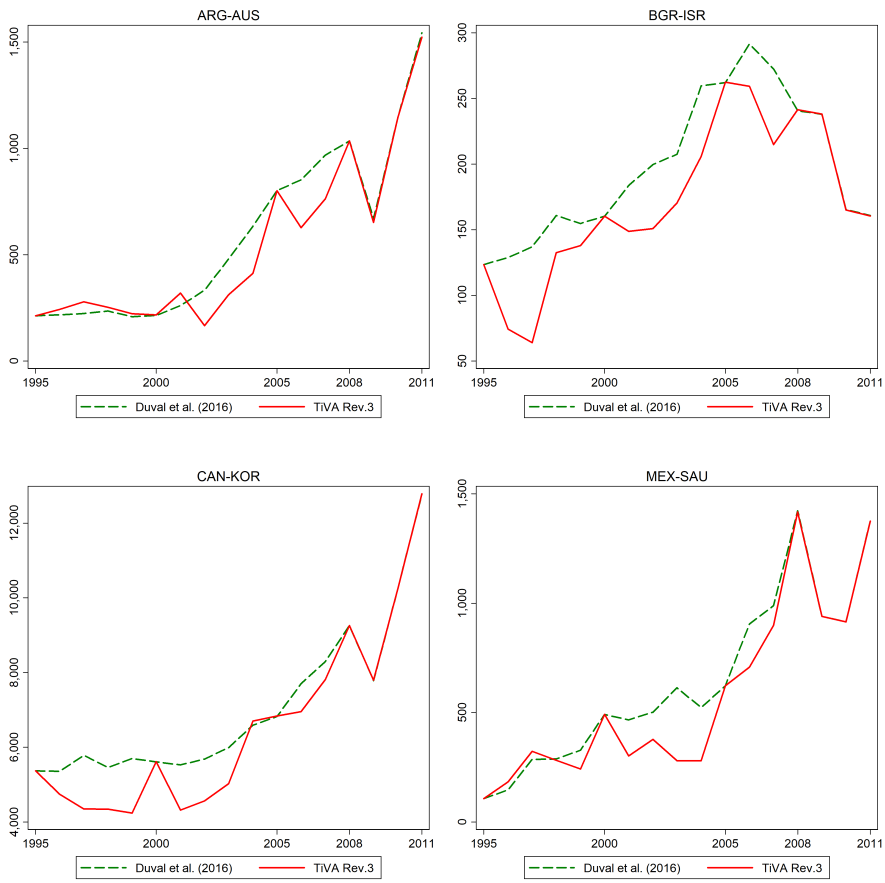
The main purpose of this paper was to reassess the causality between DVA trade intensity and BCS, which has been recently studied by a few literatures, based on the fact that gross exports can no loger capture the pure amount of DVA. By solving the problems found in the previous studies, this paper empirically identified the accurate effect of DVA trade intensity on BCS. Based on Table from 4 to 9, the main findings are summarized as follows.

First, the significant trade channel that affected output comovement between countries was not the trade intensity, but the intra-industry trade. While the DVA, total DVA, and net RDV trade intensity had no significant effect on BCS, the DVA and total DVA intra-industry trade had a positive and robust impact on output comovement even at 1% significance level. Second, in the case of net RDV, whose effect was not theoretically established, it proved to be not important from an empirical point of view. The presence of net RDV had little effect on the estimates of total DVA trade intensity, and the effects of net RDV trade intensity and intra-industry trade itself were insignificant even at 10% level. Third, regardless of types of empirical model, the financial intensity had a negative impact on BCS at 1% significance level. On the other hand, the estimates of the other key factor, which was the similarity in production structure, varied depending on models and control variables. However, in the IV models where the attenuation bias was corrected, the similarity in production structure was found to be a significant variable.

Nevertheless, a few limitations remain in this paper. First, a solid theoretical formulation of the impact of DVA on BCS is required. Although Johnson (2014) and Duval et al. (2016) suggested a theoretical path, there were many assumptions and constraints that were far from the actual transaction in the world. Second, more financial data need to be collected.

1.6 Appendix

1.6.1 Measurement Error in Duval et al. (2016)



Source: Author's construction.
Note: The four graphs are randomly selected among 903 country-pairs to visualize the inherent ME in constructed DVA by Duval et al. (2016). The dotted green line indicates the used DVA in Duval et al. (2016) while the red line is the DVA from the TiVA Revision 3. ARG, AUS, BGR, ISR, CAN, KOR, MEX and SAU denote Argentina, Australia, Bulgaria, Israel, Canada, Korea, Mexico and Saudi Arabia, respectively.

Figure 2: Difference between Duval et al. (2016) and TiVA Revision 3

1.6.2 Decomposed Terms in Gross Exports

Table 10: Decomposed Terms in Gross Exports from Country s to r

Category 1: Domestic Value-Added (DVA)

Term	**Label**	**Description**
1	DVA_FIN	DVA embodied in final exports
2	DVA_INT	DVA in intermediate exports used by direct importer r to produce local final products
3	DVA_INTrexI1	DVA in intermediate exports used to produce intermediates that are re-exported to third countries for production of local final products
4	DVA_INTrexF	DVA in intermediate exports used by r to produce final products that are re-exported to third countries
5	DVA_INTrexI2	DVA in intermediate exports used by r to produce intermediates that are re-exported to t for the latter's production of final exports that are shipped to other countries except country s

Category 2: Returned Domestic Value-Added (RDV)

Term	**Label**	**Description**
6	RDV_FIN	DVA that returns home via its final imports from r
7	RDV_FIN2	DVA that returns home via final imports from third countries
8	RDV_INT	DVA that returns home via its intermediate imports and used to produce domestic final products
9	DDC_FIN	DVA embodied in its intermediate exports to country r but returns home as its intermediate imports, and used for production of its final exports
10	DDC_INT	DVA in intermediate exports to country r that returns home as intermediate imports and used for production of its intermediate exports

Category 3: Foreign Value-Added (FVA)

Term	**Label**	**Description**
11	MVA_FIN	FVA from the importer r embodied in final exports
12	OVA_FIN	FVA from other countries t embodied in final exports
13	MVA_INT	FVA from the importer r embodied in intermediate exports, which are then used by r to produce its domestic final goods
14	OVA_INT	FVA from third country t embodied in intermediate exports, which are then used by country r to produce its local final goods
15	MDC	FVA from the importer r embodied in intermediate exports to produce its exports
16	ODC	FVA from third country t embodied in intermediate exports to produce its exports to the world

Note: The gross exports are the aggregate of DVA, RDV and FDV. The author reorganized the table by referring to Wang et al. (2013).

1.6.3 Industrial Sectors in WIOT

Table 11: Industrial Sectors in WIOT

WIOT	Code	Description
r1	A01	Crop and animal production, hunting and related service activities
r2	A02	Foresty and logging
r3	A03	Fishing and aquaculture
r4	B	Mining and quarrying
r5	C10-C12	Manufacture of food products, beverages and tobacco products
r6	C13-C15	Manufacture of textiles, wearing apparel and leather products
r7	C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
r8	C17	Manufacture of paper and paper products
r9	C18	Printing and reproduction of recorded media
r10	C19	Manufacture of coke and refined petroleum products
r11	C20	Manufacture of chemicals and chemical products
r12	C21	Manufacture of basic pharmaceutical prodcuts and pharmaceutical preparations
r13	C22	Manufacture of rubber and plastic products
r14	C23	Manufacture of other non-metallic mineral products
r15	C24	Manufacture of basic metals
r16	C25	Manufacture of fabricated metal products, except machinery and equipment
r17	C26	Manufacture of computer, electronic and optical products
r18	C27	Manufacture of electrical equipment
r19	C28	Manufacture of machinery and equipment n.e.c.
r20	C29	Manufacture of motor vehicles, trailers and semi-trailers
r21	C30	Manufacture of other transport equipment
r22	C31-C32	Manufacture of furniture; other manufacturing
r23	C33	Repair and installation of machinery and equipment
r24	D35	Electricity, gas, steam and air conditiong supply
r25	E36	Water collection, treatment and supply
r26	E37-E39	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services
r27	F	Construction

(Continued on next page)

WIOT	Code	Description
r28	G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
r29	G46	Wholesale trade, except of motor vehicles and motorcycles
r30	G47	Retail trade, except of motor vehicles and motorcycles
r31	H49	Land transport and transport via pipelines
r32	H50	Water transport
r33	H51	Air transport
r34	H52	Warehousing and support activities for transportation
r35	H53	Postal and courier activities
r36	I	Accommodation and food service activities
r37	J58	Publishing activities
r38	J59-J60	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
r39	J61	Telecommunications
r40	J62-J63	Computer programming, consultancy and related activities; information service activities
r41	K64	Financial service activities, except insurance and pension funding
r42	K65	Insurance, reinsurance and pension funding, except compulsory social security
r43	K66	Activities auxiliary to financial services and insurance activities
r44	L68	Real estate activities
r45	M69-M70	Legal and accounting activities; activities of head offices; management consultancy activities
r46	M71	Architectural and engineering activities; technical testing and analysis
r47	M72	Scientific research and development
r48	M73	Advertising and market research
r49	M74-M75	Other professional, scientific and technical activities; veterinary activities
r50	N	Administrative and support service activities
r51	O84	Public administration and defence; compulsory social security
r52	P85	Education
r53	Q	Human health and social work activities
r54	R-S	Other service activities
r55	T	Activities of households as employers; undifferentiated goods and services producing activities of households for own use
r56	U	Activities of extraterritorial organizations and bodies

Note: The author reorganized the table by reffering to Nations (2008).

2 Dynamic Interdependence of Stock Returns Based on Information Transmission: Evidence from China and Latin America

2.1 Introduction

The influence of Chinese economy has grown to a level that cannot be ignored in Latin America and the Caribbean (LAC). On trade side, the sum of Chinese exports and imports was expanded 29.36 times from 1996-2000 to 2017. Specifically, the rapid increase of raw material imports from LAC was one of the main driving forces to recover their economic situation in the 2000s. In addition to the volume of trade, the Trade Intensity Index (TII)[26] also rose 2.04 times over the same period, meaning that the trade relations became more important in consideration of the partner's importance in the world trade system. With respect to investment, LAC was the second recipient of Chinese Outward Direct Investment (ODI), and the proportion even increased from 15.3% in 2016 to 21.4% in 2017 when all the proportions of the other regions fell. Given the physical distance between them, it was a salient point. The amount of portfolio investment was $7.2 billion in 2017. Since the Coordinated Portfolio Investment Survey (CPIS) only reports it for China in 2015, 2016 and 2017, the long-term change is not able to be figured out. When it comes to labor market, both the dispatched labor of contracted projects and labor services increased 1.82 and 9.83 times from 2011 to 2017, respectively. As a result, the remittance amount from LAC to China also grew 2.26 times during the same period. In terms of money and finance, the most prominent phenomenon was the dramatic expansion of loan volume. From 2005 to 2018, the China Development Bank granted

[26]"The TII is used to determine whether the value of trade between two countries is greater or smaller than would be expected on the basis of their importance in world trade.", Trade Indicators, accessed May 19, 2019, https://wits.worldbank.org/wits/wits/witshelp/Welcome.htm.

$115.3 billion for 43 loan cases and the China Export-Import Bank lent $25.8 billion for 46 cases. The most recipients were Venezuela ($67.2 billion) and Brazil ($28.7 billion) and sectors were energy ($96.9 billion) and infrastructure ($25.9 billion). Institutionally, China has had the currency swap agreements with Argentina, Brazil, Chile and Surinam. At the moment, China has the largest contract with Argentina in LAC as they agreed to expand the amount in 2018. On Global Value Chain (GVC) side, the sum of Chinese intermediate exports and imports increased 16.06 times, and the intermediate TII also grew 2.4 times from 1996-2000 to 2017. The trade cost, which consists of the weighted average among transport costs, border related trade barriers and retail and wholesale distribution costs, decreased from 178.6 in 1996-2000 to 113.0 in 2013. Taking into account on the five aspects mentioned above,[27] it is confirmed that the role of Chinese economy has continued to become more important in LAC. Thus, this paper concluded that the degree of economic interdependence between them has increased.

However, since 2015 the economic growth of China has slowed and economic uncertainty has surged. The GDP growth rate, which was 10.64% in 2010, continued to decline from 6.9% in 2015 to 6.6% in 2018. On the contrary, the Economic Policy Uncertainty (EPU) index has dramatically increased starting in September 2015 as shown in Figure 3, and it has been substantially higher than the indexes of both the United States and the world. No one can assure that an economic crisis will happen in China, but if it occurs, there will be huge fluctuations in the entire Chinese markets. Consequently, foreign markets highly interconnected to China will also undergo significant changes. The fluctuation will be larger in the financial market, particularly, in the stock market, because most of previous literatures demonstrated that the volatility of stock returns significantly increased in times of crisis. It is because of the asymmetric volatility

[27] See Table 15 in Appendix 2.7.1 for the detailed information.

effect that the volatility becomes larger when the news or information is worse. That is, the deeper the degree of interdependence with Chinese stock market is, the greater the impact of an economic crisis happened in China is transferred.[28]

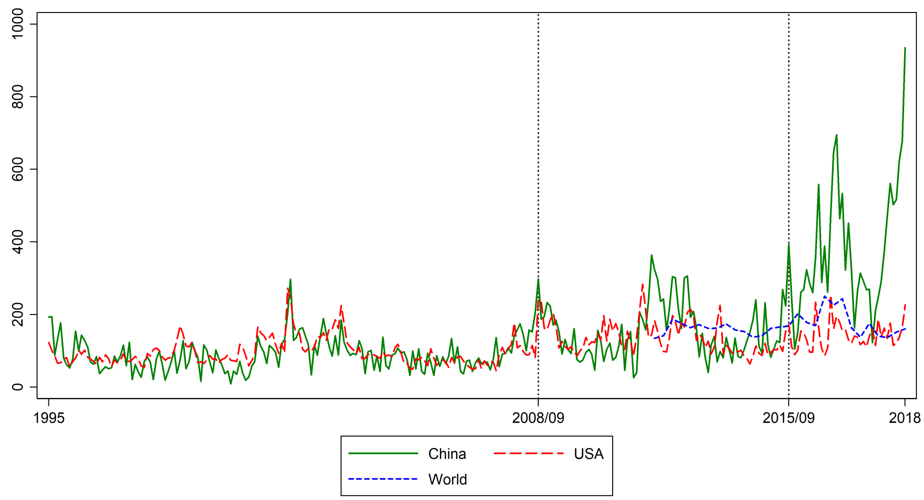


Figure 3: Economic Policy Uncertainty

In case of Asia, there are several literatures that the interrelationship of stock returns with China has intensified over time, and that the enhanced trade relations made their financial market more integrated, especially for the stock market. These results imply that there is a possibility that the stock returns between China and LAC have also been synchronized as time goes on. Thus, this paper aimed to determine whether the degree of interdependence of stock returns between China and LAC has increased over time. To perform the analysis, this paper used the Dynamic Conditional Correlation (DCC) Multivariate Generalized Autoregressive Conditional Heteroskedasticity (DCC-MGARCH) model where the information transmission process was reflected and the property of time-varying correlation was also added. It reported not only the dynamic inter-

[28]For example, a heavy fluctuation of Chinese stock returns will lead to increase the risk of investment in LAC, resulting in cash escape which causes a rapid decline in corporate investment and makes the economic situation worse in LAC. It is also important for international investors who are looking for portfolio diversification in the world.

dependence of stock returns, but also a sensitivity to new information, dependence of past volatility, and persistence of volatility. In addition, it captured a long-term trend of dynamic interdependence by using a rolling window analysis corresponding to a window width of 175 days. Finally, it derived the degree of interdependence of stock returns between the United States and LAC to figure out how LAC are relatively correlated with China.

The remainder of this paper is organized as follows. Section 2.2 provides a brief literature review about the interdependence of stock market of LAC. Section 2.3 explains the data and presents the descriptive statistics. Section 2.4 introduces the specific models and estimating process of parameters. Section 2.5 shows the estimated results of the model. Section 2.6 draws implication.

2.2 Literature Review

Despite the increasing importance of Chinese economy in LAC, only Mata and Núñez Mora (2016) analyzed about the interdependence of stock returns between China and LAC targeting Chile, Colombia, Mexico and Peru. They found that Chinese stock return was positively interconnected with Chile, Mexico and Peru, while negatively relevant to Colombia from 2000 to 2015. Nevertheless, any study about the stock returns based on the information transmission between both regions has not been accomplished yet. The main reasons for limited study are as follows.

First of all, the importance of emerging stock markets in the global market has higlighted in recent years. In other words, the earlier literatures mostly focused on the interrelationship among developed countries such as the United States, Japan and United Kingdom. They coincided in that the stock returns among them were interdependent although the degree was different depending on cases (Eun and Shim, 1989; King and Wadhwani, 1990; Lin and Ito, 1994;

Susmel and Engle, 1994; Koutmos and Booth, 1995; Fratzscher, 2002; Antoniou et al., 2003; Bartram et al., 2007). Second, the majority of studies about emerging stock markets are interconnected to developed countries or emerging countries within their own region. For instance, there are lots of literatures between China and the United States, or, China and Asian countries (Cheng and Glascock, 2006; Kim et al., 2008; Guillaumin, 2009; Huyghebaert and Wang, 2010; Moon and Yu, 2010; Kim and Lee, 2012; Fry-McKibbin et al., 2018).[29]

As above, the main interests about Latin American stock market have focused on the interdependence with the United States or within LAC. To summarize it first, Latin American stock market has had an increasingly stronger relationship with the United States, and among themselves. Christofi and Pericli (1999) reported the systematic relationship among Argentina, Brazil, Chile, Colombia and Mexico by using the Vector Autoregression (VAR) model with the innovations following an exponential GARCH process. They argued that these countries had stronger volatility spillover effect than the other regions in the world. Edwards and Susmel (2001) analyzed the behavior of volatility over time with weekly stock returns for Argentina, Brazil, Chile and Mexico. They found the deep interdependence among the countries during 1990s. Weber (2013) revealed the unidirectional volatility spillovers from the United States to Brazil and Mexico by a stochastic volatility model. Samarakoon (2011) identified the cross-market interdependence and contagion effects between the United States and emerging and frontier markets by applying VAR model with the dummy variable indicating the US crisis in 2008. Above all the emerging and frontier regions, the results between the United States and LAC was the largest from 2000 to 2009. It discovered that Latin American stock returns were significantly declined when VIX increased, and the increased VIX raised the volatility

[29]The detailed explanation for above literatures is omitted as they are not essential for this paper.

of stock returns through GARCH-type transmission process. Rejeb and Arfaoui (2016) calculated the degree of interdependence of stock returns between emerging countries, which were Asia and LAC, and the United States and Japan by using both the standard GARCH and quartile regression model. They concluded that the volatility transmission was relevant to the geographical proximity, and the structure of interdependence was asymmetric depending on the emerging countries. Sarwar and Khan (2017) analyzed the impact of US stock market uncertainty measured by VIX on Latin American stock returns before and after the financial crisis in 2008. Gamba-Santamaria et al. (2017) constructed volatility spillover indexes between the United States and Brazil, Chile, Colombia and Mexico, and among Latin American countries through the DCC-MGARCH framework. It is proved that the transmission of shock from the United States to Latin American countries increased in 2008, and the total spillover effects significantly varied from 2003 to 2016. Panda and Nanda (2017) examined the short-term dynamism and long-term equlibrium relationship of stock markets between South and Central America by a vector error corretion model, and calculated the DCC using the DCC-MGARCH model. Following the results, Chile, Peru and Venezuela were the most dynamically correlated, and the stock markets were more integrated according to the increasing DCC over time. Chuliá et al. (2017) tried to measure the response of Latin American stock markets to a shock occured in the US stock market. Using the multivariate quartile model, they found that the response were asymmetric depending on the quartiles. At the highest quartile (99%), a positive shock made Latin American return distribution positive, while negative at the lowest quartile (1%). Cardona et al. (2017) analyzed the volatility transmission between the United States and six largest Latin American stock markets by the MGARCH-BEKK model. It argued that the transmission from the United States to Latin American countries existed, but not in opposite direction between 1993 and 2013. Panda and Nanda (2018) studied on the information transmission among Argentina, Brazil, Chile, Colombia, Peru and Venezuela. They identified that the degree of correlations was higher toward the end of sample period.

2.3 Data and Descriptive Statistics

First of all, the countries selected for this paper were China (CHN), the United States (USA), Argentina (ARG), Brazil (BRA), Chile (CHL), Colombia (COL), Mexico (MEX) and Peru (PER).[30] Since LAC-6 accounted for 81% of the total GDP in LAC from 2003 to 2017, this paper concluded that it was possible to represent the whole LAC with these six countries.[31] Second, this paper applied the main stock indexes of each country, which were SHANGHAI SE COMPOSITE (SSEC), S&P 500, S&P MERVAL TR ARS (MERVAL), IBOVESPA, S&P/CLX IGPA TR (IGPA), COLOMBIA COLCAP, S&P/BMV IPC (MEXBOL) and S&P/BVLPeruGeneralTRPEN (Peru General PR).[32] Stock indexes were obtained on a daily basis, and were described in the form of a natural logarithm in Figure 4. However, the panel dataset was unbalanced due to no common national holidays or missing data. For the adjustment, this paper converted the daily stock indexes to the weekly ones as the close-to-close methodology for an unbalanced panel dataset underestimated a correlation between both stock returns (Martens and Poon, 2001).

Table 12 presents the detailed information on stock indexes and the results of the Augmented Dickey-Fuller (ADF) unit root test. The level statistics of ADF test indicated that all variables were non-stationary process as all null

[30] ARG, BRA, CHL, COL, MEX and PER are abbreviated as LAC-6 for the simplicity of notation.

[31] If adding Venezuela, the proportion increases from 81% to 87%. However, since the Venezuelan stock index moved very exceptionally due to the economic collapse, it was not included.

[32] This paper followed the notation of the Bloomberg. Stocks-Bloomberg, accessed May 19, 2019, https://www.bloomberg.com/markets/stocks.

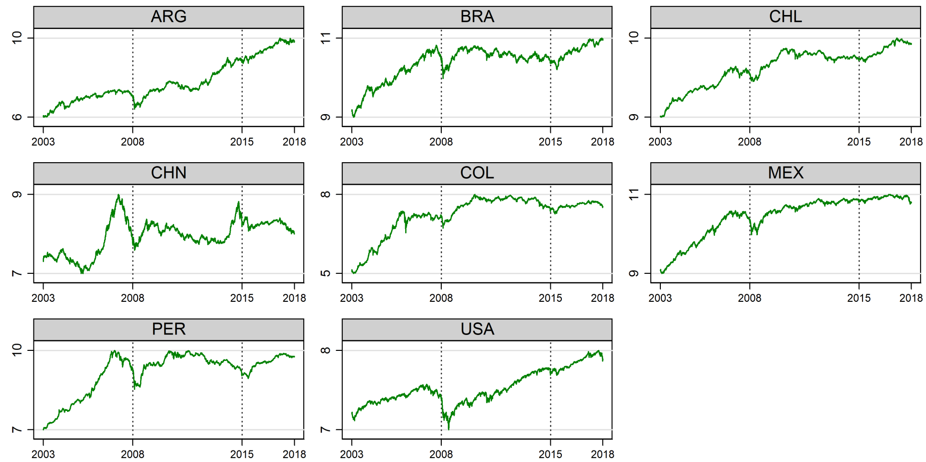


Figure 4: Natural Logarithm of Stock Indexes

hypotheses were not be rejected. Thus, this paper used the return variables derived by the first difference of logarithm of level indexes as shown in Figure 5. Contrary to the level statistics, all the adjusted variables rejected the null hypothesis even at 1% significance level that meant all return distributions were stationary.

Table 12: Information on Stock Index and ADF Test Statistics

Country	**Index**	**Sample period**	**Level statistics**	**Return statistics**
CHN	SSEC	Jan 2003 - Dec 2018	-2.037	-17.628***
USA	S&P 500	Jan 2003 - Dec 2018	-0.426	-19.301***
ARG	MERVAL	Jan 2003 - Dec 2018	0.957	-20.233***
BRA	IBOVESPA	Jan 2003 - Dec 2018	-1.518	-18.758***
CHL	IGPA	Jan 2003 - Dec 2018	-1.286	-18.142***
COL	COLCAP	Jan 2003 - Dec 2018	-2.129	-17.642***
MEX	MEXBOL	Jan 2003 - Dec 2018	-1.849	-19.056***
PER	Peru General TR	Jan 2003 - Dec 2018	-1.860	-17.082***

Note: *** for significance at the 1% level.

The descriptive statistics are summarized in Table 13. All stock return distributions were mean-stationary process around zero. CHL had the least standard deviation while CHN had the third largest one. Interestingly, the distribution of PER was positively skewed contrary to the other countries. USA had the highest kurtosis and all distributions were leptokurtic. Even though ARG had the largest standard deviation, PER had both minimum and maximum returns. The Jarque-Bera (JB) test for normality rejected the null hypothesis, and the Ljung-Box (LB) test for autocorrelation for both ten and twenty lags detected a significant autocorrelation in all cases.

Table 13: Descriptive Statistics of Stock Returns

	CHN	**USA**	**ARG**	**BRA**	**CHL**	**COL**	**MEX**	**PER**
Obs.	833	833	833	833	833	833	833	833
Mean	0.073	0.117	0.473	0.237	0.196	0.237	0.226	0.310
Std.	2.994	1.806	3.825	2.831	1.650	2.431	2.143	3.079
Skew.	-0.656	-1.339	-0.434	-0.540	-0.912	-1.029	-0.799	9.479
Kurt.	6.542	12.012	5.044	5.937	10.021	10.844	8.442	11.178
Min.	-19.341	-15.278	-20.706	-19.856	-13.760	-18.131	-15.577	-22.359
Max.	13.170	13.170	17.352	9.575	8.196	10.644	7.649	21.327
JB.	495.11^{***}	3068.18^{***}	171.23^{***}	339.96^{***}	2282.65^{***}	1826.33^{***}	1116.80^{***}	2328.71^{***}
Q (10)	83.80^{***}	31.98^{***}	53.71^{***}	43.70^{***}	64.57^{***}	64.86^{***}	29.85^{***}	154.72^{***}
Q (20)	138.38^{***}	52.05^{***}	63.64^{***}	49.73^{***}	69.41^{***}	79.98^{***}	52.00^{***}	181.22^{***}
ARCH (1)	0.198^{***}	0.266^{***}	0.156^{***}	0.156^{***}	0.033^{***}	0.404^{***}	0.162^{***}	0.171^{***}

Note: *** for significance at the 1% level. Obs. is observation, Std. is Standard error, Skew. is Skewness, Kurt. is kurtosis, Min. is minimum, Max. is maximum.

Lastly, this paper figured out whether a conditional heteroskedasticity existed. After having constructed the benchmark model where the mean equation followed AR (1) process and the variance equation was time constant, it derived residuals by applying the ARIMA (1,1) model. To identify the existence of ARCH (1) effect, the squared residuals were considered as the dependent variable and the one lagged dependent variable was used as the explanatory variable. As expected, the null hypothesis that there was no ARCH (1) effect was rejected for all stock returns. Thus, this paper assured the existence of conditional heteroskedasticity in the stock returns of all countries.

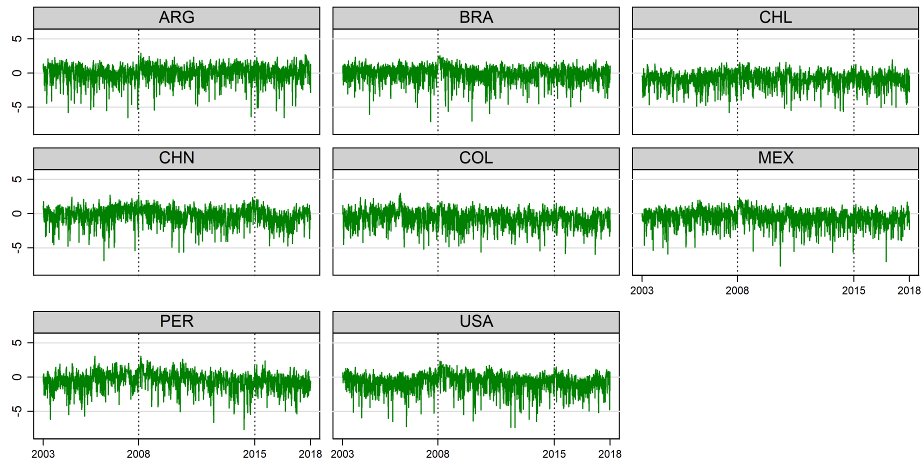


Figure 5: Stock Returns

2.4 Methodology

As shown in Section 2.3, the return distributions were leptokurtic and there was an autocorrelated conditional heteroskedasticity in the stock returns. Thus, this paper assumed that the error terms followed the GARCH (1,1) process as with most of the previous literatures, because applying a higher order p in ARCH (p) model increased the number of parameters to be estimated. Among various types of GARCH model, this paper selected the DCC-MGARCH model proposed by Engle (2002), which was estimated by two step procedure.[33]

For i = USA and CHN, and j = ARG, BRA, CHL, COL, MEX and PER, the mean equation was constructed as

$$\boldsymbol{r}_t = \boldsymbol{u}_t, \tag{7}$$

where $\boldsymbol{r}_t = [r_{it}, r_{jt}]'$ was the 2×1 stock return vector and $\boldsymbol{u}_t = [u_{it}, u_{jt}]'$ was

[33]"The DCC-MGARCH model is about as flexible as the closely related varying conditional correlation MGARCH model, more flexible than the conditional correlation MGARCH model, and more parsimonious than the diagonal vech MGARCH model.", mgarch dcc, accessed May 19, 2019, https://www.stata.com/manuals13/tsmgarchdcc.pdf

the 2×1 error term vector. The variance equation was composed of

$$\boldsymbol{\sigma}_t^2 = \boldsymbol{w} + \boldsymbol{\alpha} \cdot \boldsymbol{u}_{t-1}^2 + \boldsymbol{\beta} \cdot \boldsymbol{\sigma}_{t-1}^2,$$

where $\boldsymbol{\sigma}_t^2 = [\sigma_{it}^2, \sigma_{jt}^2]'$ was the 2×1 conditional variance vector, and $\boldsymbol{w} = [w_i, w_j]'$, $\boldsymbol{\alpha} = [\alpha_i, \alpha_j]'$ and $\boldsymbol{\beta} = [\beta_i, \beta_j]'$ were the 2×1 vectors of parameters. To apply the properties of leptokurtic distribution and information transmission process, this paper assumed that the error terms in Equation (7) conditionally followed the Student-t distribution, which was $u_t|\Omega_{t-1} \sim \text{Student} - t(0, \boldsymbol{H}_t, v)$, where Ω_{t-1} was the information set at time $t-1$, and $\boldsymbol{H}_t$ was a positive conditional covariance matrix that was

$$\boldsymbol{H}_t = \begin{bmatrix} \sigma_{it} & 0 \\ 0 & \sigma_{jt} \end{bmatrix} \begin{bmatrix} 1 & \rho_{ijt} \\ \rho_{jit} & 1 \end{bmatrix} \begin{bmatrix} \sigma_{it} & 0 \\ 0 & \sigma_{jt} \end{bmatrix} = \operatorname{diag}(\sigma_{it}^2, \sigma_{jt}^2)^{1/2} \boldsymbol{R}_t \operatorname{diag}(\sigma_{it}^2, \sigma_{jt}^2)^{1/2}. \quad (8)$$

To obtain the conditional covariance matrix in Equation (8), the following equations were constructed as

$$\boldsymbol{R}_t = \begin{bmatrix} 1/\sqrt{q_{iit}} & 0 \\ 0 & 1/\sqrt{q_{jjt}} \end{bmatrix} \begin{bmatrix} q_{iit} & q_{ijt} \\ q_{jit} & q_{jjt} \end{bmatrix} \begin{bmatrix} 1/\sqrt{q_{iit}} & 0 \\ 0 & 1/\sqrt{q_{jjt}} \end{bmatrix} = \operatorname{diag}(\boldsymbol{Q}_t)^{-1/2} \boldsymbol{Q}_t \operatorname{diag}(\boldsymbol{Q}_t)^{-1/2}, \quad (9)$$

$$\boldsymbol{Q}_t = \begin{bmatrix} q_{iit} & q_{ijt} \\ q_{jit} & q_{jjt} \end{bmatrix} = \bar{\boldsymbol{Q}}(1 - \lambda_1 - \lambda_2) + \boldsymbol{Z}_{t-1}\lambda_1 + \boldsymbol{Q}_{t-1}\lambda_2, \quad (10)$$

where $\boldsymbol{R}_t$ was the 2×2 conditional correlation matrix and $\boldsymbol{Q}_t$ was the 2×2 unconditional covariance matrix. In Equation (10), $\bar{\boldsymbol{Q}}$ was the 2×2 unconditional covariance matrix of standardized residuals and $\boldsymbol{Z}_t$ was the 2×2 matrix of standardized residuals which were expressed as

$$\bar{\boldsymbol{Q}} = \begin{bmatrix} \bar{\rho}_{ii} & \bar{\rho}_{ij} \\ \bar{\rho}_{ji} & \bar{\rho}_{jj} \end{bmatrix} \quad \text{and} \quad \boldsymbol{Z}_t = \begin{bmatrix} z_{it}z_{it} & z_{it}z_{jt} \\ z_{jt}z_{it} & z_{jt}z_{jt} \end{bmatrix},$$

where $z_{it} = u_{it}/\sigma_{it} \sim i.i.d.N(0, I_2)$. In order to maintain the positive $\boldsymbol{H}_t$ and the stationary process, the model imposed the constraints which were $\boldsymbol{\alpha}, \boldsymbol{\beta}, \lambda_1, \lambda_2 \geq 0$, $\boldsymbol{\alpha} + \boldsymbol{\beta} < 1$, and $\lambda_1 + \lambda_2 < 1$.

For the two step estimation procedure, this paper partitioned the parameter vector into two blocked vectors, $\boldsymbol{\theta} = \{\boldsymbol{\theta}_1, \boldsymbol{\theta}_2\}$, where $\boldsymbol{\theta}_1 = \{\boldsymbol{w}, \boldsymbol{\alpha}, \boldsymbol{\beta}\}$ were the volatility parameters and $\boldsymbol{\theta}_2 = \{\lambda_1, \lambda_2, v\}$ were the correlation parameters and degree of freedom. The likelihood function was constructed as follows:

$$L(\boldsymbol{\theta}) = \prod_{t=1}^{T} \frac{\Gamma[(v+n)/2]}{\Gamma(v/2)[\pi(v-2)]^{n/2}|\boldsymbol{H}_t|^{1/2}} \left[1 + \frac{u_t^{'}\boldsymbol{H}_t^{-1}u_t}{v-2}\right]^{-(n+v)/2}. \tag{11}$$

To easily use the Maximum Likelihood Estimation (MLE), a natural logarithm was applied to Equation (11). The final formula for the log-likelihood function was derived as $\ln L(\boldsymbol{\theta}) = \ln L_1(\boldsymbol{\theta_1}) + \ln L_2(\boldsymbol{\theta_1}, \boldsymbol{\theta_2})$. The equations for estimating the volatility parameters and correlation parameters were, respectively,

$$\begin{aligned} \left.\frac{\partial \ln L_1(\boldsymbol{\theta}_1)}{\partial \boldsymbol{\theta}_1}\right|_{\boldsymbol{\theta}_1 = \hat{\boldsymbol{\theta}}_1} &= 0, \\ \left.\frac{\partial \ln L_2(\hat{\boldsymbol{\theta}}_1, \boldsymbol{\theta}_2)}{\partial \boldsymbol{\theta}_2}\right|_{\boldsymbol{\theta}_2 = \hat{\boldsymbol{\theta}}_2} &= 0. \end{aligned} \tag{12}$$

However, since the volatility parameters were treated as fixed in Equation (12), the standard errors on the correlation parameters were not asymtotically efficient. To make the standard errors correct, the gradients of this estimator were given as

$$G_1(\boldsymbol{\theta}_1) = \frac{\partial \ln L_1(\boldsymbol{\theta}_1)}{\partial \boldsymbol{\theta}_1},$$
$$G_2(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2) = \frac{\partial \ln L_2(\boldsymbol{\theta}_1, \boldsymbol{\theta}_2)}{\partial \boldsymbol{\theta}_2}, \tag{13}$$

and the blocked-triangular Hessian matrix was constructed as

$$\boldsymbol{H}_T(\boldsymbol{\theta}) = \begin{bmatrix} \partial G_1/\partial \boldsymbol{\theta}_1 & \partial G_1/\partial \boldsymbol{\theta}_2^{'} \\ \partial G_2/\partial \boldsymbol{\theta}_1 & \partial G_2/\partial \boldsymbol{\theta}_2^{'} \end{bmatrix} = \begin{bmatrix} H_{11} & 0 \\ H_{21} & H_{22} \end{bmatrix},$$

and finally the correct covariance matrices for $\boldsymbol{\theta}_1$ and $\boldsymbol{\theta}_2$ were obtained from

$$\widehat{\Omega}(\widehat{\boldsymbol{\theta}}_1) = H_{11}^{-1} J_{11} H_{11}^{-1},$$
$$\widehat{\Omega}(\widehat{\boldsymbol{\theta}}_2) = H_{22}^{-1}(J_{22} - J_{21}\Psi^{'} - \Psi J_{12} + \Psi J_{11} \Psi^{'}) H_{22}^{-1},$$

where J_{ij} was the outer product of gradients matrix in Equation (13) for i and j, and $\Psi = H_{21} H_{11}^{-1}$.[34]

2.5 Results

First of all, the dynamic interdependence of stock returns between CHN and LAC-6 is represented in Figure 6. In general, LAC-6 had a positive DCC with CHN during the sample period. The dynamic pattern of ARG, BRA, COL and MEX were similar even though there were differences in magnitudes of fluctuations. The most exceptional result was PER where the dynamic interdependence has suddenly increased since September 2015. To observe the phenomenon from different perspective, Figure 7 reports the histogram of DCC between CHN and LAC-6. The distribution of BRA was a leptokurtic, which meant that the fluctuation was the most stable among LAC-6. The DCC was frequently up and down around 0.26. In case of MEX, it was quite symmetric around 0.20. The

[34] See Martin et al. (2013) for the detailed estimating process.

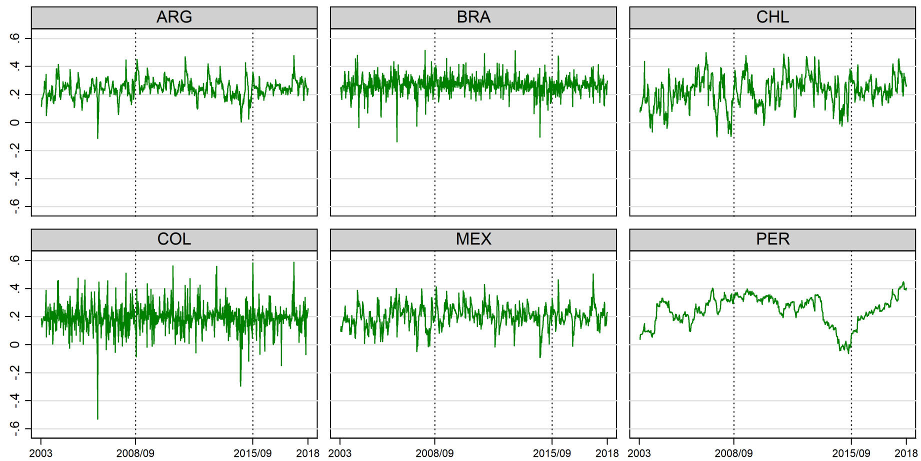


Figure 6: Dynamic Interdependence with CHN

average DCC of PER was higher than the other countries, and concentrated on the right side.

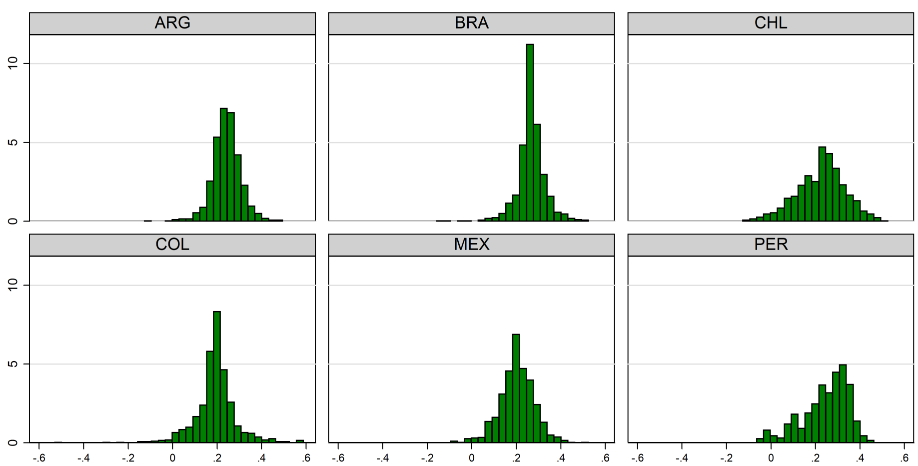


Figure 7: Histogram of Dynamic Interdependence with CHN

Second, the properties of DCC between CHN and LAC-6 are documented in Table 14. According to α_j, CHL (0.243) and PER (0.249) were relatively sensitive to new information, while BRA (0.102) and MEX (0.133) were not. Regarding β_j, the dependence of past volatility was higher in BRA (0.830) and

MEX (0.836), while relatively low in CHL (0.654) and PER (0.706). However, unlike the above results, a strong persistence of volatility, which was the aggregate of α_j and β_j, was found in all LAC-6 only except for CHL. Consequently, it can be inferred that the stock markets of CHL and PER will be more vulnerable when an economic crisis occurs in CHN. And then, fluctuations in the stock markets will last longer in PER than CHL. On the contrary, BRA and MEX will be relatively less affected by an economic shock in Chinese stock market.

Table 14: Estimated Parameters

j	w_i	α_i	β_i	w_j	α_j	β_j	λ_1	λ_2	$\alpha_i+\beta_i$	$\alpha_j+\beta_j$	$\lambda_1+\lambda_2$
ARG	0.099*	0.117***	0.875***	0.876**	0.151***	0.794***	0.042	0.741***	0.993	0.945	0.783
	(0.053)	(0.023)	(0.022)	(0.364)	(0.038)	(0.052)	(0.026)	(0.106)			
BRA	0.112**	0.128***	0.865***	0.547**	0.102***	0.830***	0.074**	0.091	0.992	0.932	0.165
	(0.057)	(0.024)	(0.023)	(0.220)	(0.029)	(0.046)	(0.043)	(0.303)			
CHL	0.114*	0.121***	0.873***	0.312***	0.243***	0.654***	0.068**	0.801***	0.994	0.898	0.869
	(0.060)	(0.025)	(0.024)	(0.108)	(0.062)	(0.081)	(0.031)	(0.089)			
COL	0.099*	0.112***	0.884***	0.268**	0.195***	0.765***	0.118***	0.052	0.996	0.960	0.170
	(0.053)	(0.022)	(0.021)	(0.107)	(0.044)	(0.050)	(0.045)	(0.218)			
MEX	0.114*	0.120***	0.872***	0.150**	0.133***	0.836***	0.058*	0.673***	0.992	0.969	0.731
	(0.059)	(0.024)	(0.024)	(0.062)	(0.032)	(0.037)	(0.032)	(0.204)			
PER	0.117*	0.121***	0.875***	0.516**	0.249***	0.706***	0.017**	0.977***	0.996	0.955	0.994
	(0.063)	(0.025)	(0.023)	(0.221)	(0.067)	(0.075)	(0.007)	(0.009)			

Note: ***, ** and * for significance at the 1%, 5% and 10% level, respectively. Parentheses are standard errors. i indicates CHN.

Third, the long-term changes of dynamic interdependence, which were constructed by the rolling window analysis corresponding to a window width of 175 days, are reported in Figure 8. BRA had a relatively time-constant DCC around 0.26, while the fluctuations were substantially large in CHL and PER. In particular, the dynamic interdependence of PER dramatically fell by about 0.30 before September 2015, but then rapidly increased again by 0.40 in 2018. Additionally, Figure 9 documents the long-term patterns of DCC between USA and LAC-6 to figure out the relative importance of Chinese stock market in LAC-6. The degree of dynamic interdependence with USA was generally higher

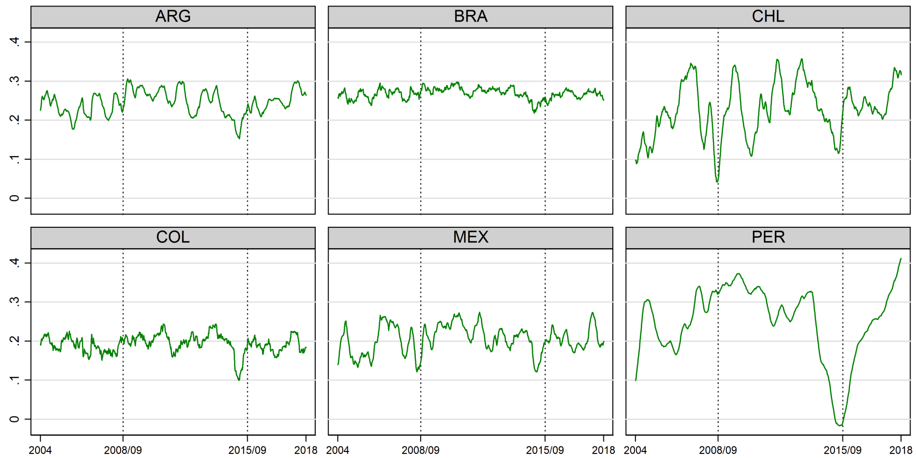


Figure 8: Dynamic Interdependence with CHN (Window: 175 Days)

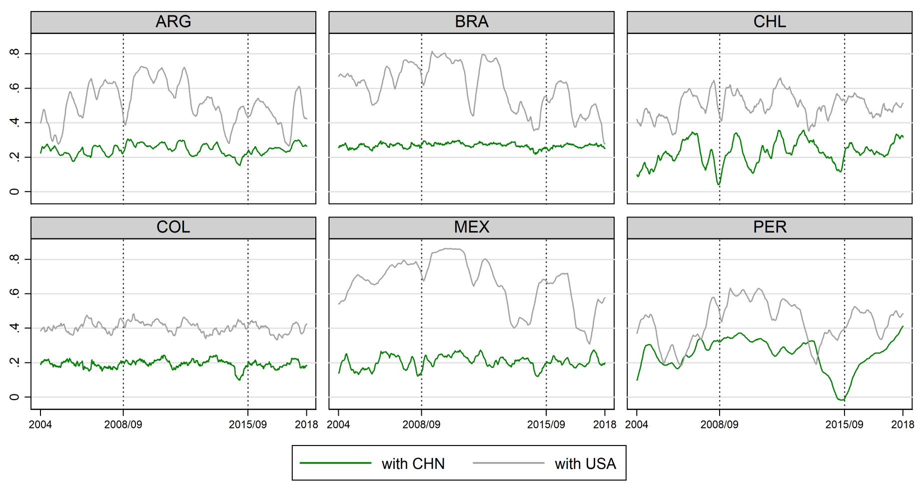


Figure 9: Dynamic Interdependence with USA and CHN (Window: 175 Days)

than that with CHN. Specifically, ARG, BRA and MEX were strongly interconnected to USA even though the degree has decreased in recent years. In CHL, the gap between USA and CHN decreased in the 2010s, but it has widened since 2015. In case of COL, it was relatively stable over time. The stock returns of PER have narrowed the difference between USA and CHN since September 2015, as the interdependence with CHN has grown.

2.6 Concluding Remarks

This paper examined the degree of dynamic interdependence of stock returns between CHN and LAC-6 because the Chinese EPU index has been increasing rapidly enough to be noticed. By using the DCC-MGARCH (1,1) model, this paper reported the changes of DCC over time, and documented the sensitivity to new information, dependence of past volatility, and persistence of volatility, respectively. In addition, it captured the long-term pattern of dynamic interdependence through the rolling window analysis corresponding to a window width of 175 days. Finally, it reported the relative importance of Chinese stock market in LAC-6 presenting the DCC between USA and LAC-6. The main findings are summarized as follows.

First of all, the Chinese influence on the Latin American stock market was not large and important, even though the economic relation between both regions has been strongly intensified over time. On average, the DCC between them was about from 0.20 to 0.30, which was not high in absolute terms. However, in case of PER, a sharp increase in the dynamic interdependence with CHN since September 2015 deserves more attention than the other countries. Second, The stock markets of CHL and PER were more vulnerable to the fluctuations of stock return in CHN, as the parameter α_j was greater than the other countries. On the contrary, BRA and MEX were less affected by an economic shock in CHN. Third, the stock market of USA was still heavily interconnected to LAC-6. In particular, ARG, BRA and MEX were strongly related to USA. In conclusion, despite the enhanced economic relation between CHN and LAC-6, their stock returns were not greatly interconnected. However, if an economic crisis occurs in CHN, CHL and PER will be more affected among the LAC-6.

2.7 Appendix

2.7.1 Economic Relation between CHN and LAC

Table 15: Economic Relation between CHN and LAC

Dimension (1)	Dimension (2)	1996-2000	2001-2005	2006-2010	2011	2012	2013	2014	2015	2016	2017
Trade	Exports ($ billion)	5.0	14.0	61.0	120.8	134.2	133.1	134.9	130.7	113.1	129.9
	Imports ($ billion)	3.7	13.9	62.3	118.6	125.1	126.4	126.0	102.9	102.4	127.3
	Trade intensity index	0.47	0.66	0.90	1.07	1.06	1.00	0.97	0.96	0.95	0.96
Investment	Outward direct investment (%)	-	-	14.6	13.0	12.8	13.0	12.0	11.5	15.3	21.4
	Portfolio ($ billion)	-	-	-	-	-	-	-	7.3	4.1	7.2
Labor	Dispatched labor of contracted project (%)	-	-	-	2.2	6.2	5.9	5.2	5.2	4.1	4.0
	Dispatched labor of labor services (%)	-	-	-	1.2	6.9	7.7	8.6	7.3	8.7	11.8
	Remittances ($ million)	-	-	123.8	147.0	144.3	303.8	330.0	328.5	316.7	331.5
Money and Finance	Loan ($ billion)	-	0.03	13.4	7.9	7.0	14.0	13.0	21.5	10.3	6.2
	Currency swaps (RMB billion)	-	-	-	-	-	190.0	260.0	282.0	282.0	92.0
Global value chain	Intermediate exports ($ billion)	1.1	3.4	13.3	25.6	27.4	27.7	30.3	28.6	24.7	28.1
	Intermediate imports ($ billion)	2.1	5.7	16.4	26.2	26.6	24.3	24.7	21.9	20.0	23.3
	Intermediate trade intensity index	0.52	0.90	1.09	1.29	1.33	1.33	1.26	1.24	1.23	1.25
	Trade cost	178.6	144.0	120.3	112.4	114.0	113.0	-	-	-	-

Source: Author's construction.
Note: Exports, import, intermediate exports and intermediate imports are from World Integrated Trade Solution (WITS). Trade intensity index and intermediate trade intensity index are calculated by author. Outward direct investment, dispatched labor of contracted project and of labor services are obtained from National Bureau of Statistics of China (NBS). Portfolio is from Coordinated Portfolio Investment Survey (CPIS). The World Bank offers Remittances. Loan is from China-Latin America Finance Database. Currency swaps are calculated by author. Trade cost is from United Nations Economic and Social Commission for Asia and the Pacific (ESCAP).

2.7.2 Conditional Variance of Stock Returns of CHN and LAC-6

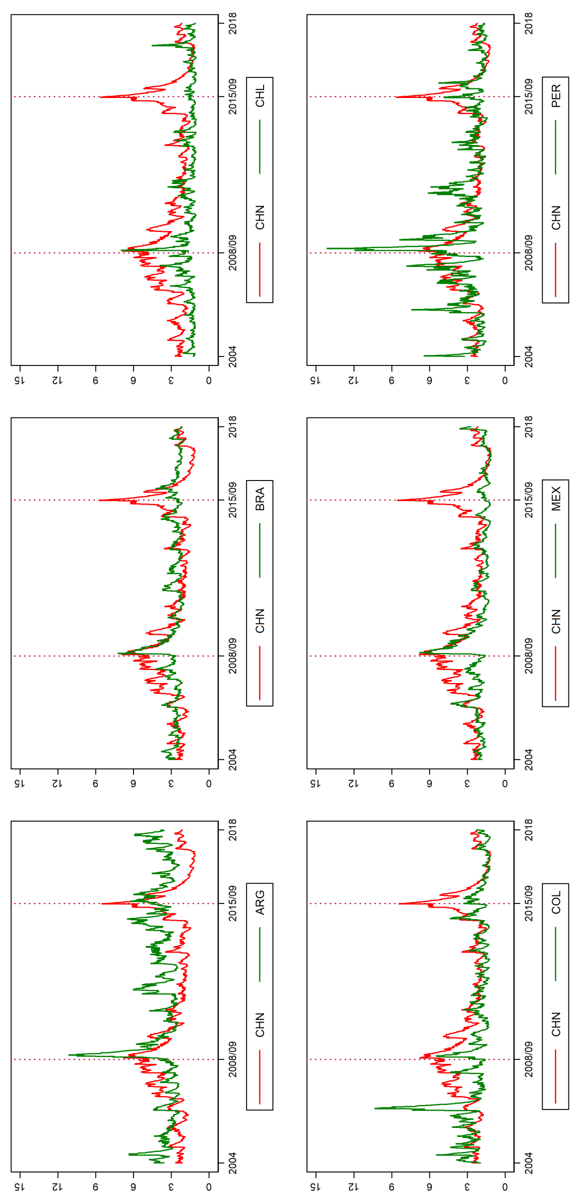


Figure 10: Conditional Variance of Stock Returns with CHN

2.7.3 Conditional Variance of Stock Returns of USA and LAC-6

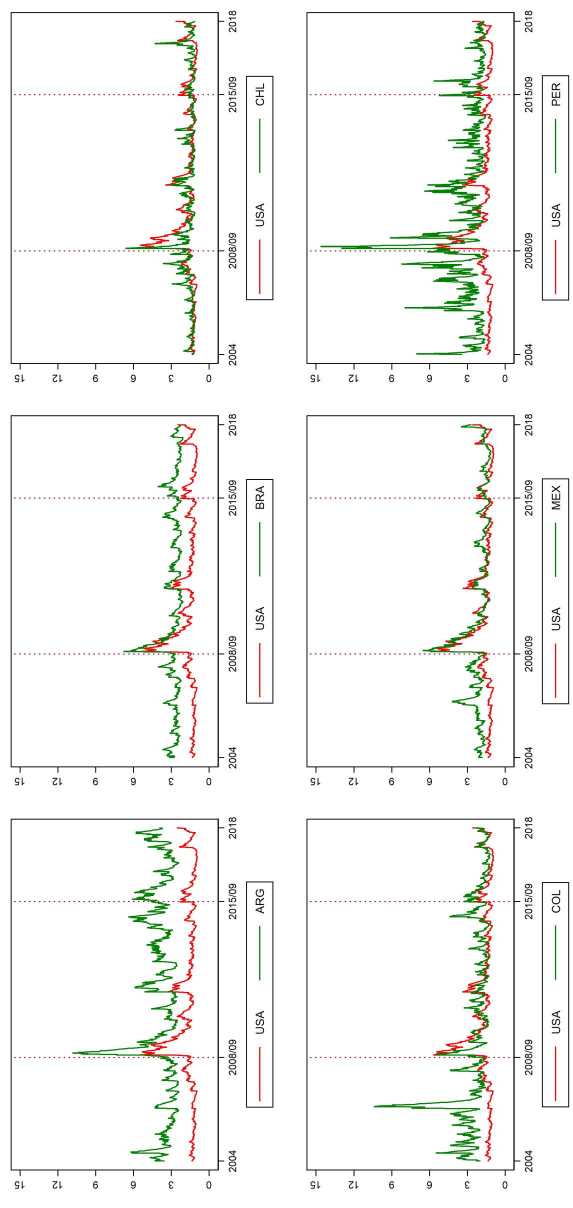


Figure 11: Conditional Variance of Stock Returns with USA

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국 문 초 록

경제통합에 관한 연구

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본 학위 논문은 국가 간 경제통합의 효과를 설명하는 두 개의 장으로 구성되었다. 1장에서는 무역 집중도와 경기변동 동조화 간 인과관계를 분석하였고, 2장에서는 주식 수익률의 동적 상호의존도를 측정하였다.

1장에서는 부가가치(Value-added)로 구성한 무역 집중도가 경기변동 동조화 현상을 유의미하게 설명하는지 실증적으로 평가하였다. 먼저 국내에서 창출한 부가가치(Domestic value-added), 국내에서 창출한 총 부가가치(Total domestic value-added), 그리고 국내로 되돌아온 순 부가가치(Net returned domestic value-added)를 사용하여 세 종류의 무역 집중도를 구축하였다. 이후 2000년부터 2014년까지 전 세계 43개국을 대상으로 최소자승법 및 2단계 최소자승법을 통해 실증분석을 실시하였다. 주요 결과는 다음과 같다. 첫째, 세 종류의 무역 집중도 모두 경기변동 동조화 현상을 유의미하게 설명하지 못했다. 둘째, 국내에서 창출한 부가가치 및 국내에서 창출한 총 부가가치로 구성한 산업 내 무역은 경기변동 동조화 현상을 유의미하게 설명하였다. 셋째, 실증분석 관점에서 볼 때 국내로 되돌아온 순 부가가치는 의미가 없었다. 결론적으로, 국가 간 경기변동 동조화 현상을 유의마하게 설명하는 부가가치 무역 경로는 무역 집중도가 아닌, 산업 내 무역이었다.

2장에서는 중국과 중남미 간 주식 수익률의 상호의존도가 시간이 지남에 따라 어떻게 변하였는지 측정하였다. 먼저 동태적 조건부 상관계수 다변량 일반화 자기회귀 조건부 이분산(DCC-MGARCH) 모형을 통해 2003년부터 2018년까지 주식 수익률의 동적 상호의존도를 도출했다. 다음으로 중남미와 미국 간 동적 상호

의존도를 통해 중남미에 중국의 주식 시장이 상대적으로 얼마나 중요한지 식별하였다. 주요 결과는 다음과 같다. 첫째, 중국과 중남미 간 경제적 관계가 다방면으로 강화되었음에도 불구하고, 중국과 중남미 간 주식 수익률의 동적 상호의존도는 낮은 수준을 기록했다. 둘째, 중국의 주식 수익률 변동에 가장 민감하게 반응한 국가는 칠레와 페루였다. 셋째, 중국과 중남미의 경제적 관계 발전에도 불구하고, 중남미 주식 수익률은 미국과 크게 연관되어 있었다.

. . . .

주요어: 경제통합, 부가가치, 무역 집중도, 경기변동 동조화, 주식 수익률, DCC-MGARCH, 중국, 중남미

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